UNIVERSITY OF SUSSEX

Essays on the Economics of Mental Health and Well-being

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Declaration

I hereby declare that this thesis has not been and will not be submitted in whole or in part to another University for the award of any other degree.

Contribution declaration

Chapter 2

I confirm that I wholly conceived of the presented idea, performed the statistical analysis, and wrote the manuscript. George MacKerron and Richard Dickens supervised the research process.

The work presented in Chapter 2 was previously published in the Journal of Housing Economics (Bencsik, 2018).

Chapter 3

This study was conceived by both authors, as well as stemming from early discussions with Nick Powdthavee, whose contribution is acknowledged. I expanded upon the original research idea, carried out data preparations, statistical analysis, and wrote the manuscript. George MacKerron contributed through discussions, exploratory analysis of the Mappiness dataset that prompted the inclusion of the data into the study, and through edits to the manuscript. Both George MacKerron and Richard Dickens supervised the research process.

Chapter 4

I confirm that I wholly conceived of the presented idea, performed the statistical analysis, and wrote the manuscript. George MacKerron and Richard Dickens supervised the research process.

Signature:

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DOCTOR OF PHILOSOPHY IN ECONOMICS

ESSAYS ON THE ECONOMICS OF MENTAL HEALTH AND WELL-BEING

SUMMARY

This thesis investigates drivers of well-being and mental health in the contemporary United Kingdom, with a particular focus on the impact of crime and the relationship with child rearing.

The first study investigates how the 2011 English riots impacted societal well-being. Using a daily response panel dataset on well-being and applying difference-in-difference analysis, I find that the riots caused widespread unhappiness across the country, especially pronounced in areas where they occurred, but present even in areas where no riot event took place. In locations where riot events occurred, their presence brought about changes in behavior as well, with an increase in watching TV and digital communication, and a decrease in face-to-face communication.

The second study investigates the relationship between well-being and the arrival of one's first child using two panel datasets and exploring the questions with a series of leads and lags. We observe a heterogeneous relationship. While longer term, cognitive well-being measures have a predominantly negative relationship with having a child, more recent, affective measures have a mixed connection, and in-the-moment well-being is pronouncedly positively associated with well-being. Gender differences are present, but in a mixed fashion, with lower well-being for women in cognitive measures and higher values in recent well-being.

The third study, using micro-level spatial panel data, estimates, for the first time in the literature, the impact of violent and sexual crimes on stress for those in the neighborhood at the per-crime level. Applying secure data from the Thames Valley region of England for 2010 to 2017, I find that violent and sexual crimes increase stress for those in the vicinity, beyond that of the impact of the neighborhood characteristics in general. Furthermore, a gap between the time of the crime and the increased stress response, suggests the presence of a mediator of information. Collecting news data, I find that one of the channels is likely news media, where if a crime-related article is on the cover page of a daily newspaper, nationwide stress levels significantly increase.

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Contents

Chapter 1

Introduction

This thesis sets out to study well-being and mental health in the context of the contemporary United Kingdom. The first paper addresses the impact of external societal factors, specifically violent public disturbances on well-being and mental health. The second paper addresses the relationship between life choices and well-being, specifically during the period of the arrival of one's first child. Meanwhile, the third paper turns back to external societal factors, and within that crime, focusing on how nearby violent crimes impact societal mental health.

The economic costs of mental ill health and ill-being are enormous — approximately half of the population in high- and middle-income countries suffers from a mental health condition at some point in their lives, while actions to combat the problem are deficient even in countries with the highest incomes (Trautmann et al., 2016). Among non-communicable diseases, mental health ties with cardiovascular diseases as the leading economic burden worldwide, and the global cost of mental illness is approximately $2.5 trillion, according to the World Economic Forum (Bloom et al., 2012). The direct costs of ill mental health alone put it among the top five costliest medical conditions in the United States, measured by expenditures (along with heart conditions, cancer, trauma-related disorders, and asthma). It also had the biggest increase in the number

of individuals with expenditures on the condition, nearly doubling from 1996 to 2006 in the United States (Soni, 2009). According to Layard (2005), the gap between our understanding of mental ill health in economic research and the cost of mental ill health is immense, for example, in comparison to our economic understanding of unemployment, which now is a smaller economic problem in terms of costs than mental health and ill-being. Moreover, two-thirds of the economic costs of ill-being are considered to be indirect costs, such as lost income and productivity (Bloom et al., 2012). In light of this, it is especially important to understand what societal impacts like crime play in contributing to poor outcomes, and how well-being changes around the arrival of one's first child.

The contribution of this thesis is threefold. First, it brings non-financial costs to the center of economic analysis. Economists long held these non-financial costs to be as large as financial costs when considering some externalities (see for example Becker (1968) in relation to crime), and various aspects of it have been addressed in the economic literature, however with an understanding that a complete estimation is still out of our reach. The thesis hopes to contribute to moving towards such completion. Second, by discussing both mental health and well-being, it brings two fields that are predominantly addressed through separate research strands together (see further below). Third, the thesis provides estimates of societal well-being and mental health by using unique panel datasets never combined before, among others (a) data on well-being reported in the moment of experience, the gold standard of information collection (Kahneman et al., 2004), (b) extensive and detailed crime data, for the first time in economic research connected with mental health information at such granularity, (c) representative, population-wide survey data, and (d) newly-collected data on news reporting.

In early neoclassical economics assumptions of pleasure and pain were central, and it relied heavily on experimental psychology, from which it did not have a strict separation

initially (Bruni and Sugden, 2007). Later, neoclassical economics moved away from this, focusing on preference satisfaction and positivism within economic science. With that, the relationship with psychology also nearly disappeared, and well-being was discussed in other social sciences, if at all, for example as part of the social indicators movement (Hicks et al., 2013). Then, in the 1970s both behavioral economics as well as discussions on subjective well-being emerged, reconnecting the two fields to some degree. Tversky and Kahneman (1974) and Easterlin (1974) are often considered as the two beginning points of these processes, respectively. Today, Layard (2006) argues that economists can and should contribute meaningfully to the study of well-being.

Meanwhile, psychiatry initially was concerned with the study and treatment of mental disorders and diseases, thus it focused on a negative state to avoid, rather than a positive to reach. Only in the middle of the 20$^{\text{th}}$ century did the term "mental health" emerge, with its positive direction of valuation (Bertolote, 2008). Today, mental health is considered either separate from or encompassing of psychiatry. The economic valuation of mental health is even newer, and even though Campbell (2004) defines mental health as a state of psychological well-being—highlighting just how strongly linked the two topics are—, the two economic research strands largely remained and continue to remain separate, addressed through often separate channels. While well-being is often considered its own sub-field within economics, mental health is most often categorized under the broader field of health economics.

Both fields, however, rose to more prominence in recent years, and the United Kingdom (UK) took a leading role among developed countries in measuring societal well-being when in 2007—after having measured social indicators for 40 years—it started to consider what data exists and how better well-being could be measured. Then, recognizing that existing data is limited, the Office for National Statistics set out to measure the three key aspects of well-being in 2010, launching the ONS National Wellbeing Programme (Steel, 2016). The program was explicitly intended to complement existing

economic measures, and it measures (a) evaluative well-being: satisfaction with life and its domains, (b) affective well-being: recent positive and recent negative feelings, and (c) eudaimonic well-being: how meaningful and worthwhile one considers one's life to be (Hicks et al., 2013).

The measurement of well-being was coupled with the explicit intention to implement the results in policy making, and to consider national well-being along with economic growth in monitoring the country. The formation of the All Party Parliamentary Group on Wellbeing Economics in 2009 was one of the first steps in this direction. This cross-party group of MPs and Lords seeks to "highlight how wellbeing serves as a valuable and pragmatic framing for making policy decisions and for setting a vision for the UK." Meanwhile, the What Works Centre for Wellbeing, an initiative designed to inform evidence-based policy decisions, was formed in 2014 as part of the What Works Network. The Centre uses a network of academics, government departments, and non-profits to collate evidence and make that accessible for policy decision-making at the local and national level.[1]

Meanwhile, the first time the ONS addressed the question of mental health with a dedicated publication was in 2015, and there are only four publications available to date on the topic by the ONS, none covering the whole population, but only specific segments. There is more focus on the topic within the National Institute for Health and Care Excellence (NICE), another What Works Network member, where questions around mental health receive attention regularly.[2] Meanwhile, the National Health Service's (NHS) introduction of the program Improving Access to Psychological Therapies (IAPT) in 2008, which was largely the benefactor of and reason for the NHS' tripling of

[1] See more here about the aforementioned initiatives as well the source of the quote: https://wellbeingeconomics.co.uk/, https://whatworkswellbeing.org/about/about-the-centre/, https://www.gov.uk/guidance/what-works-network

[2] NICE's Evidence Collection contains nearly 30,000 items on mental health, ranging in categories from Guidance and Policy through Primary Research to Information for the Public. https://www.evidence.nhs.uk/

its mental health budget, now offers not only greater access to mental health services, but also a broader access as well, designed to be encouraging for people with mental health issues at all degrees of seriousness to access it (Clark, 2011). The expansion of the mental health budget, however, only came after a long period of the population being underserved, where even in 2005 only 5% of those with a mental illness have seen a psychiatrist or psychologist in the past year, and mental disorder was the single leading health cause among workers in the UK to go on incapacity benefits (Layard, 2005). Overall, while mental health access has improved in recent years, its movement towards an important national outcome, being able to supplant economic indicators as well-being indicators do, and the field of mental health economics gaining traction, has been slow. Therefore, it is also the aim of this thesis to bring well-being and mental health economics under one roof, considering them as outcome measures side by side.

The thesis addresses the outcome of well- and ill-being in two contexts, that of the impact of crime and that of the arrival of one's first child. The study of the relationship between criminality and well-being or mental health originates in questions around the mental health of perpetrators of crime (Wessely and Taylor, 1991), and still today the clearest calculation on the crime-related cost of mental health is through the calculation of the proportion of crime costs due to events with perpetrators with such illness (Layard, 2017). Later, the additional focus on victim mental ill-being emerged (Miller et al., 1993), along with the study of crime's mental health impact on society as a whole. However, economic calculations of such societal costs are limited still today. It is the intention of the thesis to contribute to that through the first and third papers. Meanwhile the middle paper, exploring the relationship between the arrival of a newborn and a multitude of well-being outcomes contributes to studies on the importance of non-pecuniary returns to one of the financially costliest life choices made by individuals at a large scale.

The first paper of the thesis, titled "The non-financial costs of violent public dis-

turbances: Emotional responses to the 2011 riots in England" explores the impact of the 2011 riots on well-being across the UK. The riots, which took place over five days in August 2011, were the largest riots in the United Kingdom in decades, however the understanding of how they affected citizens is limited. Due to riots' unpredictable nature and rare occurrence, even international studies on the not directly financial costs of riots to society are lacking. I provide new evidence on the question using data on the exact time and location of every riot event that took place across the country—from a publicly available dataset collected by *The Guardian*—combined with data on well-being with the exact location and time of the response from the Mappiness panel dataset (MacKerron, 2012). Using difference-in-difference estimates, I find that respondents in Local Authorities with at least one riot event suffered decreased happiness and increased stress levels compared to their own reports during the previous five days. The difference-in-difference approach, the controls applied, as well as the fact that no other national event occurred at the time that could have provided a concurrent quasi-experimental treatment, suggest that the relationship is likely causal. Furthermore, even those in areas without riots exhibited a significant pattern of ill-being. The full effect of the riots was substantial: in affected areas it was equal in size, but in the negative direction, as the well-being effect of Christmas Eve in the positive one. The negative effect of the riots also did not cease when the riots ended, but persisted at least until the end of the summer. Lastly, behavioral changes also occurred: individuals in areas with riots increased their information-seeking and digital communicating behaviors, while they communicated less in person.

The second paper, titled "Not quite a bundle of joy: Well-being losses and gains when entering parenthood" addresses the relationship between the arrival of one's first child and well-being. The question has received prior attention in economics—predominantly through works focusing on singular or composite index-based well-being outcomes—but studies have often drawn contradictory conclusions. Here, the contribution of the thesis

is two-fold. First, the current study measures the impact of the arrival of the first child on a multitude of outcomes, highlighting the multifaceted nature of the association. Secondly, the study, acknowledging that becoming a parent is a decision that has long-term patterns, therefore, the study estimates the pattern with a series of leads and lags from three years before birth to eight years after it. Applying two panel datasets, the British Household Panel Survey and Mappiness, the chapter addresses the relationship between the newborn's arrival and two distinct measures of well-being: cognitive and affective. Specifically, we measure how well-being in the years immediately before, during, and following the first child's arrival differ from childless years in terms of satisfaction with eight domains of life and with life overall, as well as with an extensive set of measures of recent well-being, using the General Health Questionnaire. Additionally, for the first time in the literature, we provide estimates of the impact of children in the very moments of being with children or engaging in childcare. While instantaneous (or close-to instantaneous) measures of well-being from the time of stimuli are considered the gold standard (such as the Day Reconstruction Method) (Kahneman et al., 2004), there is no evidence to date on this question. Using the two datasets and the range of outcome variables, we find that the arrival of the newborn is predominantly negatively associated with most cognitive measures, while mixed-to-positively associated with affective measures, with notable gender differences.

The third paper, "Stress on the sidewalk: The mental health costs of close proximity crime", addresses the impact of crime as well, but now shifting the attention from unusual crimes, such as the 2011 riots to more common, regularly occurring crimes. Combining Mappiness data with extremely micro-level data on every reported crime occurring in the Thames Valley Police area, the paper is able to estimate the impact of crime on mental health at a highly precise level. The paper uses secure data from 2010 to 2017 to identify the time and location of every reported crime, and finds that individuals in the spatio-temporal vicinity of violent and sexual crimes exhibit substan-

tively increased stress levels. The estimates, due to location, time, and individual fixed effects being applied, are likely to be an unbiased estimate of the impact of crime on well-being, thus providing initial evidence on the per-crime cost of violence on mental health in the case of non-unusual crimes. Secondly, the paper is also the first to provide estimates of the dissipation of the impact of crime, finding that it is violent crimes within the past three days and within the same Output Area—the size of a street, with an average of 131 households—that drive the results. Additionally, I observe a temporal gap between treatment and response, such that it is crimes specifically two and three days before the response, and not crimes the day before, that lead to the change in mental health. Observing the gap, I hypothesize the presence of a mediator of information, and discuss the possible channels with a particular focus on news media. To test whether news might be a channel—that, is whether news about crime impacts stress—I scrape news article data from three leading daily newspapers, and find that if a crime-related article is a cover-story then nationwide stress levels are significantly increased.

The question of how much stress reports at a time of responding can reflect possible longer term mental health changes is important, especially for the third paper of the thesis. Stress is often differentiated falling into three categories: extreme, one-off stressors; individual, socio-economic stressors; and ongoing, daily life event as stressors (Ingram and Luxton, 2005). Stress discussed in the third paper is closest to the third type of stress category, where crime in the proximity is a non-extreme, but regularly recurring stress source. While studies to date have predominantly focused on extreme, rare types of crimes (such as terrorist attacks, and such as the examination of the impact of the riots in the first paper), there is extensive evidence that daily stressors can also contribute negatively to mental and physical health outcomes. For example, Morales and Guerra (2006) find individuals scoring high on a composite index of local crime related stressors and family stressors exhibit a higher likelihood of depression

and aggression. Meanwhile, Sharkey et al. (2014) find that local violent crime leads to worse test scores for children. Lastly, it is also important to address the impact among particularly sensitive populations. For example, among pregnant women Huizink et al. (2003) find that increased levels of daily hassles during the first trimester lead to lower development scores for the baby. In sum, while it is unlikely that each daily stressor would have a long-running negative consequence alone, it is exactly the kind of repeated exposure that characterizes local crime that can sum to substantial negative outcomes.

Overall, the thesis sets out to more completely estimate how external factors as well as individual decisions lead to well- and ill-being, doing so in order to more precisely estimate the mental health and well-being costs of economic phenomena previously largely considered only in their financial aspects.

Chapter 2

The non-financial costs of violent public disturbances: Emotional responses to the 2011 riots in England

2.1 Introduction

Riots are a series of violent acts against the existing social order (Lachman, 1996). Over the course of five August days in 2011 in the United Kingdom (UK), a total of 224 locations—shops, streets, squares—experienced rioting. Many businesses were severely affected, and property damage was widespread. The citizens of UK lived through these days either directly experiencing the riots in their neighborhood, or through watching the news as the events unfolded on TV. The riots had direct monetary costs in terms of extra policing, property damage, and the substantial number of additional cases dealt with by the judicial system. However, the riots also had beyond-monetary costs – the negative, non-financial costs citizens experienced through this heightened social tension.

Using Mappiness (MacKerron, 2012), a smartphone application that collects data on happiness and stress levels, I provide an estimation of the direct in-process emotional

impact of riots on citizens for the first time in large-scale applied research. Doing so, I find that the disturbances substantially increased unhappiness and stress throughout the UK. The negative effect did not remain localized to areas with riots, but functioned as a blanket coverage throughout the entire country, with especially pronounced effects in the treated areas. In areas with riots, the events led to a 5% reduction in happiness and a 6.8% reduction in relaxation, a similar sized effect to Christmas Eve being cancelled; more specifically, the riots had the equal effect in the negative direction as Christmas Eve has in the positive direction for the average citizen. The negative effect persisted until the end of the summer, and 'placebo riots' imposed at various earlier times in the same summer show that the impact was unique to the actual occurrence time.

Local neighborhood characteristics, specifically the racial makeup of the neighborhood, were associated with a heterogeneity in the effect of the treatment. Respondents in areas with the top 25% largest share of white residents were particularly unhappy, even with no riots happening in the vast majority of these localities. Similarly to the effect of crime, the riots also induced behavioral changes. TV watching grew substantially across the country, along with digital communication, such as texting, email, and social media use increasing and in person communication decreasing in areas with riots. Overall, the English riots of 2011 brought about substantial unhappiness and stress for the average resident of the United Kingdom. The non-financial costs were widespread and included those further from the riots as well, leading to a nation-wide negative, beyond-monetary impact.

2.2 Background

Personally experienced violence has long-lasting, beyond-monetary impacts on the individual, such as on the education performance of pupils (Sharkey et al., 2014). However,

violence that is not individually encountered can have repercussions too. The 9/11 terrorist attacks in the United States, beyond greatly affecting Americans, even caused a well-being loss in the British population (Metcalfe et al., 2011). Similarly to the terrorist attacks in the USA, the London subway bombings in 2005 increased the stress levels of Londoners, with people also reporting changes in their behavior (Rubin et al., 2005). Meanwhile, intangible costs, such as fear and anxiety, have been documented to be associated with local crime levels (Dustmann and Fasani, 2016; Braakmann, 2012; Ross and Mirowsky, 2001; Jackson and Stafford, 2009), but due to the unpredictability of riots, associations between well-being and exposure to riots are much harder to measure, and it is a connection that has been sparsely studied so far. One exception is Hanson et al. (1995)'s study analyzing the aftermath (though surveying only 6 months after the events took place) of the 1992 Los Angeles riots, which finds that people in the areas affected experienced extensive psychological distress and, specifically, post-traumatic stress disorder.

The English riots of 2011 took place between 6–10 August, marking a week of violence that affected half the boroughs of London and another 20 cities across England. Starting in the neighborhood of Tottenham, in the North London borough of Haringey, each day the riots expanded to additional boroughs and then further cities, reaching a national scale by 8–10 August (Moore, 2011). Two days prior to the riots, on 4 August, a 29-year-old Black Londoner named Mark Duggan was shot and killed by police in the same borough in which the riots started. Duggan was perceived to have a firearm when shot according to police, but a subsequent police investigation concluded that Duggan did not have any weapon on him at the time (Laville et al., 2011). On Saturday, 6 August, Duggan's family and friends organized a peaceful protest ending at the local police station in Tottenham (Briggs, 2012). With around 300 attendees originally, the protesters demanded that a sufficiently high ranking police representative to speak with them, and when that didn't happen, they remained outside of the station longer

than planned. Around dusk, additional people joined, and the protest took a violent turn. Duggan's family and others from the original protest left at this time, while the remaining crowd looted and burned shops overnight.

Daylight hours were quiet the following day, 7 August, but looting occurred again after dusk, with hundreds of people joining in. Police were deployed to the scenes of the looting, but could not contain it, especially since looting spread to multiple locations within London. The next day was quiet, but the night saw Britain's heaviest rioting in decades. In addition to looting, a person was shot and another attacked during the riots, both dying of their injuries, and multiple buildings and two double-decker buses were set alight. The next day, 9 August, the police were deployed at three times the scale of a normal day, which, just like in the case of crime at other times (Draca et al., 2011), resulted in reduced overnight violence. On the last day, 10 August, a hit-and-run killed three people in an area affected by riots. Aside from that, the riots had practically died down, and only a few additional incidents subsequently took place. In the aftermath, Bell et al. (2014) find that there was a disproportionately severe sentencing by the criminal justice system for crimes related to the riots.

Based on participant interviews in the aftermath (using a sample of arrested and not arrested riot participants) the majority of the rioters were male (79%); unemployed (among those who were not students, unemployment was 59%, compared to the national level of 8% for the same time period); young (29% aged 10–17, 32% aged 18–20, and 16.5% aged 21–24); and largely non-White (47% Black, 5% Asian, 17% mixed/other, and 26% White) (Lewis et al., 2011). The exact number of participants is unknown, but more than 4,600 people were arrested (Draca et al., 2011), and of that, 2138 people were convicted by the courts of various offense by August 2012, a year later (Ministry of Justice, 2012).

Participants said that they were motivated by a combination of the immediate opportunity to gain material possessions and by long-term social factors that impacted

their lives. Many mentioned "lack of opportunities," "disappointment with the system," and "unfair stop and searches" as their motivation. Research by Kawalerowicz and Biggs (2015) finds that there was a preexisting difference in treatment by the police. Areas where prior to the riots people felt disrespected by police saw more rioters coming from them, while areas with good police relations had fewer rioters. The research also revealed that rioters came disproportionately from disadvantaged areas and were poorer. Lastly, there were striking differences in integration into society between the rioters and the general population. Although the vast majority of rioters were British citizens (86% of those sentenced to prison, the only sub-population for which data is available) (Ministry of Justice, 2012), only 14% of those interviewed said they really felt a part of British society (the national average was 53% at the time)(Lewis et al., 2011).

"This is criminality, pure and simple, and it has to be confronted and defeated." So said David Cameron, the UK's Prime Minister during the riots (Telegraph, 2011). According to him, "we know what's gone wrong ... a slow-motion moral collapse ... irresponsibility, selfishness, behaving as if your choices had no consequences" (BBC News, 2011). Kenneth Clarke, the then justice secretary, talked about "criminal classes," suggesting that the majority of participants were reoffender criminals, "cut off from the mainstream in everything but its materialism" (The Guardian, 2011). "These thugs," as Mr. Cameron put it in this interpretation, caused the vast majority of the country to become victims to a crime of a few.

Social science research conducted in the aftermath came to somewhat different conclusions. Briggs (2012) in his analysis of participant interviews suggests that frustration and the lack of opportunities "made them a population quite ready to counteract their structural position in an effort to send a message." Qualitative research based on interviews with rioters found tensions with police were crucial (Lewis et al., 2011). The interviews talked about an "anger at what was felt to be discriminatory treatment,"

and the shooting before the riots was considered a symbol of the perceived injustice.

2.3 Data

2.3.1 Mappiness

The Mappiness dataset (MacKerron, 2012) is a large voluntary sample of the UK population. It is administered through a smartphone application that anybody can download for free and prompts respondents usually twice a day.[1] After providing personal information when signing up,[2] people fill out how happy, relaxed and awake they feel, with whom and where they are, and what they are doing at randomly prompted times. While they can join and leave at any time, respondents in 2011 took part for a median of 61 days (that is, two months), producing a rich panel with daily responses that is unusual in its scale.

The question on happiness ('relaxedness') is phrased, "Do you feel happy (relaxed)?"; the respondent can answer on a sliding scale with one end point denoted as "not at all" and the other as "extremely." An advantage of the phone application is that it doesn't anchor the question with visible numbers, but with a sliding scale on which respondents can select any point that the phone's pixels can register. A continuous variable is created using this scale. For the purpose of the analysis, the results are scaled between 0 and 100 afterwards, offering a much finer gradient of responses than most surveys allow. Focusing on the momentary happiness of individuals as opposed to their life satisfaction also contributes to the growing literature estimating causal effects on well-being using this metric. Momentary happiness, the affective counterpart of evaluative

[1] While there are plenty of responses from other countries, the paper only uses ones given at any location within the United Kingdom. This also helps avoiding Mappiness participants on foreign holidays influencing the results. Responses also have separate information for when the prompt occurred and when the respondent completed the questions. If these two took place more than 60 minutes apart, then I exclude them because a probability sample of response moments is required, and moments when people choose to respond (rather than happen to be prompted) are unlikely to be random.

[2] The demographic information – such as whether someone is married or employed – provided at signing up is treated as constant over the period of weeks considered in this research.

life satisfaction, is gaining traction in the literature, such as with recent research on the relationship between work and happiness (Bryson and MacKerron, 2017).

Respondents also report at each prompt what activities they are undertaking at the time of answering. From a list of 40 options (and "Something else") people can choose one or multiple options that describe their immediate situation. For example, one individual on the third day of the riots reported that they were "watching TV" at the time of answering; another person was "talking, chatting, socializing," "drinking coffee, tea," "texting," and "browsing the Internet." In particular, activities related to communication and information seeking will be of interest here, as the literature on crime (which is similar to the riots in their violent nature) and research on natural disasters (which is similar to the riots in their unpredictability and rare nature) suggest that individuals are most likely to change such behaviors (Becker and Rubinstein, 2004; Perry et al., 2001).

2.3.2 Weather and daylight information

The British Atmospheric Data Centre's Met Office Integrated Data Archive System (MIDAS) provides hourly spatio-temporal information for the respondent's momentary GPS location on various measures. These include wind speed, air temperature, sunshine duration, and rain measurements.[3] These are used as controls to avoid attributing weather effects on well-being to the riots. Daylight information for each date and location comes from R's *StreamMetabolism* package.

2.3.3 Information on the riots

The Guardian newspaper collected a list of all confirmed riot events as the riots were unfolding and compiled a publicly available dataset of 245 events.[4] Each entry contains

[3]See more on weather data here:
http://catalogue.ceda.ac.uk/uuid/220a65615218d5c9cc9e4785a3234bd0

[4]http://www.theguardian.com/uk/datablog/2011/dec/06/england-riots-shops-raided#data

information on the day (and, for about a third of them, also on the specific hour) of the riot event, the location given as an address (or sometimes a shop name), and a short description of the event. Table 2.1 contains a list of all events categorized by criminal law based on severity,[5] as an overview. If one description contained two different types of crime, such as a shop that was looted and stolen from, then it is put into the more severe category. When excluding the shooting of Duggan that occurred two days before the riots and served as a catalyst for the riots, as well as locations in the "Other" category, a total of 224 treated locations remain.

The geographical unit most suited for analyzing the localized effect within the UK is the level of Local Authority. Local Authorities (LAs) are units of local government, usually the size of a city district or a smaller town. London, for example, has 33 Local Authorities. This geographical unit allows analyzing reasonably small areas to estimate a localized effect, as well as enough Mappiness responses from the neighborhood for empirically meaningful analysis, something that couldn't be done if only considering the very street or block treated. Therefore, I identify each specific location's associated LA and find that nationwide the events occurred in 39 Local Authorities.[6]

2.3.4 Information on local population race

The proportion of non-white participants in the riots was disproportionate to their representation in the population; however, interview participants did not consider the riots to be "race riots." This tension makes it particularly interesting to focus on how people responding from areas with the highest portion of each racial and ethnic group reacted to the riots. To capture racial characteristics, we have to exploit finer data

[5]Severity of each event is determined based on categories used by the Home Office, except for criminal damage being divided into two categories, arson, and all other criminal damage. This is done so that arson, a particular characteristic of riots, clearly shows in magnitude in comparison to other cases. The classification was done by evaluating each short description provided in The Guardian dataset. The categorization was reviewed by a lawyer for accuracy.

[6]Events in the "Other" category all occurred in areas with actual riot events, so including or excluding these events in terms of determining treated neighborhoods doesn't influence the analysis.

Figure 2.1: Map of riot locations in London, and overall in the UK

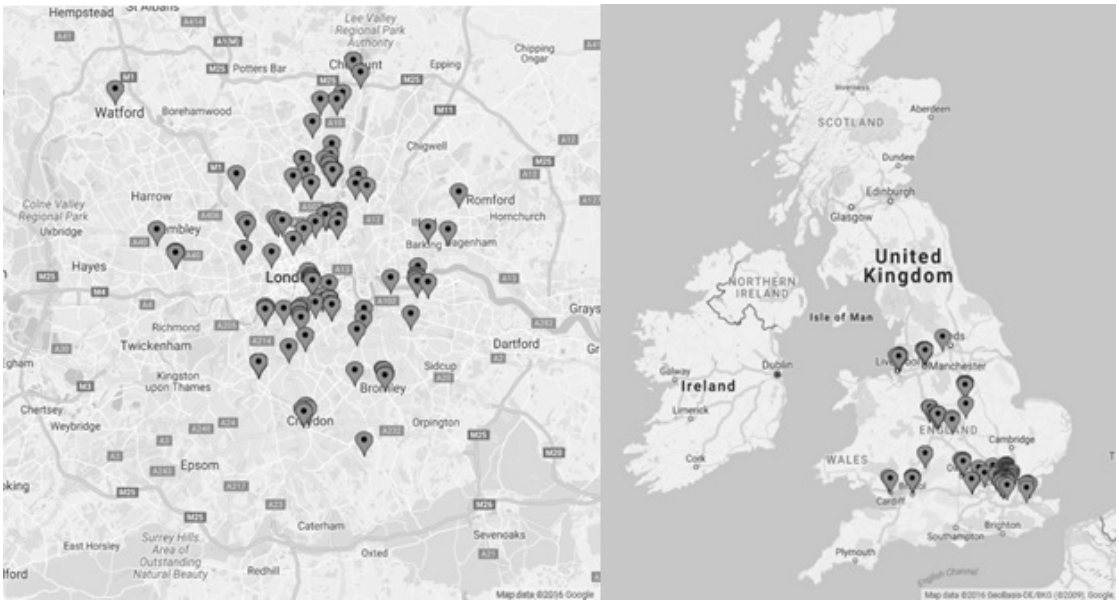


Table 2.1: Type and frequency of riot-related crimes

Crime type	Number of events	Examples
Violence against the person	22	Murder, stabbing, clash with police with injuries in some cases
Arson	51	Fire lit on buildings, cars, shops, bins
Criminal damage (excluding arson)	80	Windows, windscreens smashed, shops damaged, cars attacked
Acquisitive crime	58	Shops looted, raided
Disorder	14	Groups gather, vandalism, graffiti
Other	20	Roads closed off, evacuation due to risk

than from Local Authorities, because race divisions tend to have particularly sharp geographical divides. Therefore, I use the geographical unit of Lower Layer Super Output Areas (LSOA). LSOAs have about 1,500 residents, on average, and usually make up a few city blocks, or a part of a smaller town. They are compact areas that are more likely to encompass similar individuals. London, for example, has 4,835 LSOAs (as opposed to 33 LAs). I focus on areas with the top 25% highest proportion of each racial and ethnic group within England and Wales, using census data current as of March 2011–just a few months before the riots.[7]

2.4 Empirical strategy

The Mappiness data is unique in that it provides information on the riots' effects while the riots took place, as opposed to most research that has to use post-event measures to approximate effects. As there is data on the effects of the treatment for the process of the treatment taking place, I compare in the analysis respondents' level of well-being from before the riots to during them. The time of "treatment" is defined as the 5 days of the riots (Saturday to Wednesday), and the time before the treatment as the 5 days before the shooting of Duggan (Saturday to Wednesday again), leaving out the Thursday and Friday between the two categories. On the first of these two excluded days, Mark Duggan was shot, and on the second the news of the shooting spread, both of which directly led to the protest and riots, so these days are excluded for not being strictly "before treatment."

According to the news at the time and The Guardian dataset with riot events, the riots only started around nightfall on each of the five days. Sunset in London on 6 August 2011 (the first night of the riots) occurred at 8:41 p.m., and dusk is usually about 30–35 minutes long. Therefore, in the analysis, I categorize all responses from an area with riots starting there that evening as untreated until 10 p.m., and treated

[7]The data can be accessed here: https://www.nomisweb.co.uk/census/2011/qs201ew

from 10 p.m. onward. From a location experiencing riots on a given night, all following responses within the five days were then considered treated; once an area was exposed to the riots, it remained affected according to the specification regardless of the hour of the day. To measure the impact of the riots, I apply a difference-in-differences model where for individual i in area a at time t:

$$Y_{iat} = \alpha_i + \beta R_a + \gamma T_{ait} + \epsilon_{iat} \tag{2.1}$$

where α_i is the individual fixed effect, R_a is a set of location fixed effects controlling for the unique characteristics of each Local Authority in the United Kingdom, while the interaction term, T_{ait} is the treatment variable taking up 0 for responses the five days before the events, 1 for responses during the events from Local Authorities where riots were not present (yet), and 2 for responses from Local Authorities where riots already broke out. Because each area experienced riots from a different day onward during the five days of the riots, the treatment term takes the value 2 from different days onward depending on the location.

Let me illustrate the empirical strategy with an example using three different Local Authorities in London. The Local Authority of Bexley didn't experience any riots, so the treatment term is 0 for the first 5 days and 1 (ongoing riots but not there) for the second set of five days. Haringey, where the riots first broke out, experienced riots naturally already on the first night, so the treatment term is 0 for the pre-period, 1 for the daytime of the first day, and takes the value of 2 from 10 pm on the first day, and for the full four more days of the riots. Camden, however, was free from riots for the first two days, and only had riots starting on the third. Consequently, the treatment term for responses from Camden is 0 for the pre-period of five days, 1 for the first two days of the riots, and until 10 pm on the third, and then 2 for the night of the third, and the whole of the fourth and fifth days. In sum, this way I am able to compare the baseline pre-period to how responses in areas with riots changes, as well as how responses with

no riots there but with ongoing riots elsewhere in the country changed–put simply, I differentiate the localized and the spillover effects of the riots.[8,9]

2.5 Descriptive statistics

There is a total of 12,731 responses from the United Kingdom for the five days of the riots and the five days prior to them, evenly split between the preceding five and the five during the riots. 23% of these fall into LAs where at least one riot event happened. These responses come from a total of 1,308 individuals who responded at least once in the 5 days before and at least once during the quasi-experiment period. The sample average for happiness was 68.2 on a 0 to 100 scale, while for relaxation it was 66.9 (see further descriptive statistics for the outcomes and control variables in Table A1).

Because Mappiness is a smartphone application and as smartphones were not in such widespread use in 2011, one expects respondents to be better off than the public in general. Indeed, the median household income among participants is £48,000, while in the UK population in 2011 it is £23,208.[10] The gender balance of the sample is identical to that of the population, with 51% being female.[11] The median age is 39 years in the UK, while 33 among the participants, and likely due to that, the percentage of households with children is substantially different (57% in the population[12], 30% among participants). Finally, employment levels are eight percentage points higher

[8]I note that the spillover effect to be attributed to the riots hinges on the assumption that no other event took place during the riots that could have influenced people across the country. This assumption is supported by research, finding that the riots were the main news item during the time and received "blanket coverage in the UK media" (Reeves and de Vries, 2016).

[9]An alternative way to approach the difference-in-differences estimation would be comparing the whole of the UK to Ireland (or England, Wales, and Scotland to Northern Ireland). However, the number of responses in these locations in the observed short time frame of the riots is insufficient for such a comparison.

[10]Measuring National Wellbeing http://www.ons.gov.uk/ons/rel/wellbeing/measuring-national-well-being/life-in-the-uk–2014/art-mnwb–life-in-the-uk–2014.html?format=print

[11]Source for gender and age information: Office for National Statistics, 2011 Census. http://www.ons.gov.uk/ons/rel/census/2011-census/population-and-household-estimates-for-the-united-kingdom/stb-2011-census–population-estimates-for-the-united-kingdom.html#tab-Key-points

[12]Labor Force Survey http://www.ons.gov.uk/ons/publications/re-reference-tables.html?edition=tcm%3A77-328237

among Mappiness respondents compared to the general population (70%[13] to 78%).

The Mappiness is not a nationally representative sample, and these differences are partially due to who the individuals are who could afford a smartphone in 2011. But this is also due to the fact that the Mappiness heavily oversamples Londoners (39% of respondents are Londoners, while Londoners are only 12% in the UK population). This being the UK's richest city with a strong presence of young, working people, the differences to the national average are understandable. This oversampling also carries an advantage though, because the riots also disproportionately occurred in London Local Authorities (20% of London LAs had at least one riot, while only 5% of LAs elsewhere), so the sampling of Mappiness is helpful in accessing a sufficient sample of respondents close to the riots.

In the analysis, the riots are considered a treatment that affects respondents. However, for the results to be valid, it is a prerequisite that the riots do not affect participation. Various robustness checks show such an effect is not present. For example, participation rates before and during the riots are unchanged, so it's not the case that the exogenous variable of interest would have influenced attrition, people didn't join less, or leave the study earlier because of the riots. People also took the same length of time from prompt to response before and during the riots, Thus, there is no significant difference for an individual in their signal-to-response time. Unanswered signals were also not exhibiting any peaks during the riots. Over the course of 2011, the signals left unanswered grew steadily, likely because the Mappiness application was rolled out in late 2010, and by mid-2011, people were slightly less active in taking part. This pattern occurs when comparing the proportion of unanswered signals before and during the riots too. However, it is rather than reflecting behavior during the riots interpreted as part of a trend in its use.

The other aspect of rioter-survey participant interactions could be whether any

[13]Office for National Statistics http://www.ons.gov.uk/ons/rel/lms/labour-market-statistics/october-2011/statistical-bulletin.html

individuals belonged to both groups. While this cannot be completely ruled out, it is extremely unlikely because of the relatively small size of the two groups and the difference in average demographics. While certainly not definitive proof, there was no response recorded at a riot location and during a riot. Furthermore, the riots also didn't alter the proportion of responses coming from one's home, the same amount of people chose to be at home as before. There was, however, a slight increase in the proportion of responses coming from one's home LA, but not a change in the proportion coming from urban versus rural areas. Overall, people didn't seem to flee large cities, nor close their front doors for days, but just stayed somewhat closer to home than usual. Finally, I also did not observe a change in country-wide happiness levels in the six months preceding the riots. It could still be the case that for certain subgroups there was a growing unhappiness that might have contributed to the riots. However, to test that, one would have to make assumptions about who they are, and that implies analysis beyond the scope of this paper. What can be noted here is that, overall, the country didn't exhibit any trend in happiness levels that could have suggested the riots were "brewing" at a large scale.

2.6 Results

I compare responses from prior to the riots to during them and find that they had a substantial localized effect as well as a meaningful spillover in other areas of the country. According to Model (3) in Tables 2.2 and 2.3, being in a Local Authority once riots started there leads to a 3.51 percentage point decrease in happiness and a 4.68 percentage point increase in stress for an individual. To interpret, this would mean a drop in happiness of 5% and in relaxation of 6.8% compared to the sample averages in Local Authorities with riots, and a 1% decrease in both outcomes in areas without riots, assuming linearity.

Table 2.2: The happiness effect of the riots

	(1) Happy	(2) Happy	(3) Happy
Baseline: During the 5 days prior to the riots			
During the riots in areas where riots already happened	-3.22***	-3.14**	-3.51***
	(1.28)	(1.35)	(1.12)
During the riots in areas with no riots (yet)	-0.27	0.055	-1.16**
	(0.50)	(0.60)	(0.52)
Clustered standard errors: Local Authority	Yes	Yes	Yes
Clustered standard errors: individual	Yes	Yes	Yes
Day of the week fixed effects	Yes	Yes	Yes
Local Authority fixed effects	Yes	Yes	Yes
Circumstantial controls		Yes	Yes
Individual fixed effects			Yes
Constant	77.8	93.9	85.3
N	12,731	12,731	12,731

The baseline time period is July 30th to August 3rd 2011. The treatment time period is August 5th to August 10th 2011.
Respondent sample size in Model (3): 1,308.
Circumstantial controls: Weather: air temperature, sunshine duration, wind speed, rain; Response given during daylight or not; Hour of the day; Response sequence.
Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table 2.3: The stress effect of the riots

	(1) Relaxed	(2) Relaxed	(3) Relaxed
Baseline: During the 5 days prior to the riots			
During the riots in areas where riots already happened	-4.91***	-5.28***	-4.68***
	(1.41)	(1.44)	(1.24)
During the riots in areas with no riots (yet)	-0.36	-0.50	-1.54**
	(0.55)	(0.67)	(0.60)
Clustered standard errors: Local Authority	Yes	Yes	Yes
Clustered standard errors: individual	Yes	Yes	Yes
Day of the week fixed effects	Yes	Yes	Yes
Local Authority fixed effects	Yes	Yes	Yes
Circumstantial controls		Yes	Yes
Individual fixed effects			Yes
Constant	78.7	62.5	46.2
N	12,731	12,731	12,731

Models defined as above.

It is not entirely straightforward to interpret the magnitude in terms of comparisons because most of the Mappiness data is related to personal, in-the-moment actions. In search of another national level experience to which we could compare the riots, we could look at sports. I find that the riots were at least twice as bad as when the English soccer team lost on penalties in the semi-finals to Italy in the 2012 UEFA European Championship (it was a significant country level happiness loss of -1.42 percentage points, suggesting that while this certainly was not a global event, it did have a strong impact in the UK). Alternatively, we could look at religious holidays. Here, the challenge is that we are comparing the size of a positive impact (in the case of holidays) to the size of a negative one (the riots), which is somewhat similar to paralleling a willingness to pay calculation with a willingness to avoid one. Accepting this limitation, one could say that for people's happiness the riots were more impactful in the negative direction than how impactful Christmas Eve is in the positive one (Christmas Eve contributes 3.29 percentage points to happiness).

On a personal level, having riots in the area a person responds from is as bad as

reporting to be working $\beta = -3.78$ at the time of response, the second most negative activity people ever report (after being sick in bed). Similarly, being near where riots were going on is about twice as bad as commuting or traveling $\beta = -1.81$ at the time of the response. These latter examples are particularly telling of the severity of the riots, because they were able to induce a happiness loss matching or surpassing the effect of certain activities while they are directly underway by the individual, even though most respondents were not in physical contact with the riots. Both of these types of comparisons suggest that the riots were a large negative externality for citizens close to them in proximity.

In robustness tests first I run falsification tests to asses whether the pattern observed emerges at other times too. I impose a "placebo riot" on the same locations 4 weeks, 8 weeks, and 12 weeks before the actual riots and compare the results to 4, 8, and 12 weeks before the pre-period. I find these results largely insignificant, though I do observe some unhappiness 8 weeks before compared to 9 weeks before, possibly hinting at some dissatisfaction leading up the riots (see Appendix).[14] Next, I ask whether the spillover effect is truly a spatial spillover to areas where riots never happen, or it is driven by responses from areas where riots have not broken out yet, but will. Separating these two sets of observations using postestimations, I find them to be insignificantly different from each other. This suggests that a similar level of heightened ill-being was present in both areas before riots broke out there and in areas that never ended up experiencing riots. This finding is in line with the impression at the time that the riots were spreading unpredictably, and it was not unexpected for them to occur anywhere in the country.

Next, I test whether certain groups were more affected, finding no significant differences in the level of impact for those having low income (£16,000 per annum and

[14]Given the riots might have been predated by local changes in well-being, as well as having changed local well-being in its wake, a closer to ideal falsification test would apply results from a year before the riots, for August 2010. However, sufficient Mappiness data for the time is not available, thus this estimation is not possible to conduct.

below), those young (25 and below), and those living alone. I do however find that men were unhappier than women during the riots in areas without riots—meanwhile, there were no gender differences in areas with riots. Next, I ask whether the location of the response attenuated some of the effect, finding that the impact was less strong in areas (i.e., the happiness loss was not so substantial) during the riots if somebody responded from a Local Authority without riots which was their home Local Authority than if they responded from not their home LA. This might suggest that staying close to home was reassuring for individuals. Testing whether specifically being within one's home mattered, I find that it did not, suggesting that it was mostly staying in one's familiar neighborhood or town, but not staying inside one's home that drove this result. Lastly, I find that during the riots people responses less from outdoors (and more from indoors) both in locations with and without riots. The avoidance of public spaces is in line with behavior exhibited in relation to fear of crime, where for example Janke et al. (2016) find that outdoor walking as an exercise is negatively impacted by local crime rates.

Lastly, I turn to focusing on the persistence of the effect of the riots. Here, I compare my initial pre-period (the five days before the riots) to the week after, two weeks after, and three weeks after. Generally, I find that the impact of the riots dissipated within two to three weeks (see Appendix), however, it is hard to put a precise date on the dissipation, as three weeks after the riots was the very final days of August, leading into a new season, as well as heading back to school and to work for many. Therefore, comparing happiness levels mid-summer to the very end of it leads to at best imprecise estimates, where as the impact of the riots lessened other concerns might have taken afoot for many.

Next, I ask whether areas with certain populations report larger effects than others. Specifically, focusing on local population race and using triple differences, I find that respondents in English and Welsh LSOAs with the top 25% largest share of white

residents and where there were no riots were particularly unhappy and stressed compared to respondents in riot-free but less homogeneously white areas (see results in Appendix). These results are specifically driven by responses from areas that never ended up experiencing a riot. Meanwhile, I don't find particular patterns for LSOAs being in the top 25% of the distribution in terms of any other race and ethnicity.[15]

Next, I ask whether the in process well-being changes reflect what we know retrospectively —that the riots were an urban phenomenon. Research suggests that the riots manifested more often in spaces where rioters routinely passed through and which were closer to their homes (Baudains et al., 2013). Furthermore, urban areas with a high proportion of young people and a shorter distance to shops and malls were more likely to experience riots (Kawalerowicz and Biggs, 2015). Indeed, almost all treated LAs are urban, so I cannot meaningfully compare rural and urban locations with riots. However, even if I compare areas without riots that were urban and that were rural, I find no differences in the changes in well-being levels compared to before the riots. This suggests that people in rural places were just as stressed and 'unhappy' as those in cities.

The riots are also considered an English phenomenon. Out of the 225 riot events, 223 happened in England, and 2 in Wales. Research written in the aftermath refers to the events as "English" (as opposed to "British" or "in the United Kingdom") riots (see titles such as "The English Riots of 2011," "The August riots in England," "Reading the riots: investigating England's summer of disorder" of works referenced earlier). Just as above, English versus Welsh, Scottish, and Northern Irish LAs with riots cannot be compared due to sample size restrictions, however, if I compared English and non-English areas with no riots compared to their own levels the week before, I find that the time of the

[15]Another way to assess the importance of demographic characteristics would be to look at those Mappiness users who are characterized by these themselves, as opposed to focusing on the location characteristics where they respond from. There is no data in Mappiness on race, but there is on employment. Unfortunately, the unemployed group is too small to give meaningful results when restricting the analysis only to them.

riots had a significantly indifferent effect for people in all areas of the United Kingdom. The combination of findings on no different in urban and rural areas and in England and outside of it further reinforce the notion that while the riots were happening they did not exhibit a clear geographical pattern; residents across the countries were similarly unhappy about them going on, however unaffected their type of location might have turned out to be, looking back on it.

2.6.1 Behavioral Changes

With quantitative research on riots and citizen behavior lacking, I turn to two other areas of study for forming hypotheses on possible behavioral changes. Crime, an activity similar to the riots in its violent form, and natural disasters, similar in their unpredictability and rareness, provide guidance for possible behavioral changes, which suggest a likely increase in communication and in information consumption (Becker and Rubinstein, 2004; Bourque et al., 1993).

Table 2.4: Activity changes in areas with and without riots

	(1) Watching TV	(2) Texting, email social media	(3) Reading	(4) Browsing the Internet	(5) Computer and phone games
During the riots in areas with no riots (yet)	0.025**	0.0021	0.0018	0.0022	0.0021
	(0.012)	(0.0083)	(0.0067)	(0.0079)	(0.0049)
During the riots in areas where riots already happened	0.083***	0.035*	0.0041	0.023	-0.018**
	(0.024)	(0.019)	(0.010)	(0.022)	(0.0090)
N	12,731	12,731	12,731	12,731	12,731
	(6) Talking, chatting socializing	(7) Working, studying	(8) Traveling, commuting	(9) Shopping, errands	(10) Drinking alcohol
During the riots in areas with no riots (yet)	-0.017	0.031*	-0.0052	0.0082	-0.014**
	(0.012)	(0.017)	(0.0091)	(0.0059)	(0.0064)
During the riots in areas where riots already happened	-0.039*	0.028	-0.0047	-0.0087	-0.017*
	(0.020)	(0.024)	(0.013)	(0.0085)	(0.0093)
N	12,731	7,586	12,731	12,731	12,731

Models defined as Table 2.2 Model (3).
Estimates for "Working, studying" are restricted to workdays for meaningful interpretation.

In line with these predictions, I find that TV watching increased both in areas with riots and without. Meanwhile, browsing the Internet and reading remained unchanged, suggesting that the mean source of information people likely turned to was televised news. In terms of communication, there appears to be a nearly one to one substitution, where in areas with riots technology based communication increases, while socializing decreases. Using a fixed effect linear probability model here, as in other parts of the study, the observed coefficients are marginal effects. Therefore, relative to the time before the riots, the probability of someone watching TV when responding increases by 2.5% in areas without riots, and with 8.3% in areas with riots. In the latter areas personal communication that is technology based increases by 3.5% while one that is likely face to face decreases by 3.9%.

Additionally, we observe a slight change in time devoted to gaming–maybe now spent on real world news–, while there is also a drop in alcohol consumption, which could possibly be at least partially related the decreased time spend socializing. Meanwhile, there is slight increase in working, at least in riot-unaffected areas, while we observe no change in tasks that involve having to go to public spaces, such as commuting and running errands.[16] The lack of decrease in working in areas with riots is noteworthy for it contradicting media narratives at the time. During the riots, news sources suggested that at least in London a number of businesses closed early (Newton-Small, 2011). However, not observing such a pattern might suggest such businesses were in a small minority once considering treated areas across the capital and the country.

2.7 Discussion

The contribution of the study is three fold. First, I present evidence on the impact of civil disturbances while they are going on, something not possible before due to data

[16]In a robustness test I re-estimate the change in "Traveling, commuting" only for responses given with one's home Local Authority to separate local commuting from possible vacation related travel. I find consistent results where I also don't observe a change in local commuting.

limitations. I find that the riots substantively decreased happiness and increased stress in Local Authorities (neighborhoods in the case of London, whole cities everywhere else in the Unite Kingdom) where they occurred. The impact was immediate, with results reporting lower momentary well-being throughout the riots running, and then dissipating by the end of the summer. Second, I find that it was not only areas with riots but with without were also affected, exhibiting about 1/3 of the effect size as in areas with riots. The fact that both areas near to and far from the riots were impacted suggested that the events impacted well-being at a national, and not only at a localized scale. Additionally, I also find that respondents in neighborhoods that had the highest share of white residents were particularly unhappy and stressed during the riots. Lastly, I observe behavioral changes, where TV watching increased nationally, while digital communication increased and in person communication decreased in impacted areas.

It is also important to acknowledge how much a one off event, however grievous, can have an effect on mental health. Stressors can be categorized into three categories: one off, major events; socio-economic stressors, such as growing up poor; and day to day stressors (Ingram and Luxton, 2005). The riots fall into the first category, a one-off, national event that altered well-being both in its vicinity and in areas far from where it was occurring. While the riots were not a persistent phenomenon, evidence on terrorist attacks at least suggests that such extreme, short, one off events can have lasting consequences in other aspects of life for certain sub-populations, likely channeled through the short term well-being change. For example, Camacho (2008) finds in the setting of Colombia that mothers who are pregnant when there is a landmine explosion in their municipality give birth to children with lower birth weight.

Overall, the study argues that the 2011 English riots causally led to reduced well-being measures that did not remain localized neither spatially nor temporally. In the context of the riots, focusing on unhappiness and stress also allows the consideration of all regions of the United Kingdom, as opposed to monetary costs, such as property

damage, that are inevitably localized to where riots took place. In sum, the results suggest that the riots had an additional substantial externality beyond that of financial ones.

2.8 Appendix

Table A1: Descriptive statistics

	Mean	SD	Min	Max
Happy	68.2	21.0	0	100
Relaxed	66.9	22.3	0	100
Treatment identification	0.56	0.61	0	2
Day of the week	3.77	2.32	1	7
Response Local Authority	235.1	118.0	3	406
Air temperature (in blocks)	17.0	4.10	6	26
Extent of sun in response hour	0.39	0.39	0	1
Cloudiness	4.90	2.73	0	8
Wind speed	8.58	4.46	0	29
Any rain in response hour	0.073	0.26	0	1
Response during daylight (dummy)	0.90	0.30	0	1
Hour of day (in 3 hour blocks)	14.0	4.17	0	21
Response's order among the respondents responses (in blocks)	119.1	189.9	0	1001
N	12,731			

Table A2: Falsification test for treatment: 4, 8, and 12 weeks prior

	(1)	(2)	(3)	(4)	(5)	(6)
	Happy			Relaxed		
	4 week	8 week	12 week	4 week	8 week	12 week
During the placebo riots	0.25	-0.38	-0.29	0.26	-0.67*	0.068
in areas with no riots (yet)	(0.47)	(0.38)	(0.39)	(0.46)	(0.39)	(0.40)
During the placebo riots	-0.67	-1.60**	-0.80	-0.20	-1.16*	-0.44
in areas where riots already happened	(0.59)	(0.64)	(0.60)	(0.48)	(0.62)	(0.65)
N	14558	18257	22023	14558	18257	22023

Models defined as Table 2.2 Model (3).

Table A3: Happiness and relaxation levels after the riots

	(1)	(2)	(3)	(4)	(5)	(6)
	Happy			Relaxed		
	1 week	2 week	3 week	1 week	2 week	3 week
After the riots	-1.141**	-0.725	-1.229*	-1.349**	-1.133**	-1.324
in areas where riots did not happen	(0.572)	(0.523)	(0.726)	(0.544)	(0.542)	(0.840)
After the riots	-1.438	-1.363	-1.569	-2.386*	-0.955	-2.083
in areas where riots happened	(1.101)	(1.138)	(1.151)	(1.260)	(1.370)	(1.271)
N	12610	12312	12055	12610	12312	12055

Models defined as Table 2.2 Model (3).
Model (1) and (4): July 30 to August 3 compared to August 13–17.
Model (2) and (5): July 30 to August 3 compared to August 20–24.
Model (3) and (6): July 30 to August 3 compared to August 27–31.
Note: Testing beyond August is avoided as with September multiple seasonal changes occur, and the wellbeing differences to early August aren't convincingly driven by the riots alone anymore. Therefore, persistence effects are presented until the end of August.

Table A4: Well-being changes in LSOAs with the top 25% largest population share of white residents

	(1) Happy	(2) Relaxed
Baseline: During the 5 days prior to the riots		
Areas where riots already happened	-4.08***	-4.78***
	(1.36)	(1.41)
Areas with no riots (yet)	-0.94	-1.30*
	(0.68)	(0.76)
Highest white population share	1.72	3.16***
	(1.11)	(1.19)
Areas where riots already happened * Highest white population share	2.02	3.79
	(5.14)	(2.79)
Areas with no riots (yet) * Highest white population share	-2.49**	-2.76**
	(1.16)	(1.34)
N	10450	10450

Models defined as above.

Chapter 3

Not quite a bundle of joy: Well-being losses and gains when entering parenthood

Joint work with George MacKerron

It is well-established in the economics literature that the decision to add an additional child to a family tends to involve significant monetary costs for the parents (Muellbauer, 1977; Pollak and Wales, 1979; Bourguignon, 1999). For example, it requires an approximate expense of $233,610 (in 2015 US dollars) for a middle-income, married-couple family with two children to raise a child from birth through age 17 in the United States, which translates to $13,000 in annual expenses (Lino et al., 2017). Meanwhile in the United Kingdom, annual child raising costs rose from £6,686 in 2003 to £10,822 in 2014 (Centre for Economics and Business Research, 2014). Additionally, expenditure costs alone do not capture the full costs of children, because children in the household are also associated with substantial time costs (Bradbury, 2008). Some estimates suggesting that they are even larger than the total costs of goods, services,

and housing together (Gustafsson and Kjulin, 1994). According to a recent study by Buddelmeyer et al. (2018), child birth significantly increases perceived time stress for both parents, but especially for mothers, that lasts for several years post-birth. Yet, despite the large costs associated with raising a child, having a baby continues to be one a highly desirable goal for many couples around the world. This is primarily because most prospective parents tend to expect that they will derive sufficiently high non-pecuniary benefits from becoming a parent (e.g. Folbre, 1994; Grundy and Read, 2012).

However, the notion that parents derive significantly higher utility from children is largely inconsistent with many cross-sectional studies that show parents to be, on average, no more satisfied with life than non-parents (e.g. Nomaguchi and Milkie, 2003; Evenson and Simon, 2005; Powdthavee, 2008). Direct engagement with one's own children, such as doing childcare and being with children, is not associated with higher well-being levels than doing other activities or being with other individuals. In fact, doing childcare rates at a similar well-being level as other household and work tasks (Kahneman et al., 2004). Parents also do not seem to report significantly more positive momentary experiences compared to their childless counterparts (e.g. Kahneman et al., 2004; White and Dolan, 2009). While there are some studies that have reported a positive cross-sectional relationship between life satisfaction and parenthood (e.g. Nelson et al., 2013; Kohler et al., 2005), their results either apply only to a certain group of individuals in the data—e.g., those who are residing in countries with good welfare systems—or are positive and statistically significant only when factors that are positively correlated with both parents' well-being and child birth, such as income and employment status, are not controlled for in the regression equations.

Our paper contributes to the current debate by attempting to explain what an individual experiences while becoming a parent. Our key contribution is applying a wide set of outcome variables using two long-running panel datasets in the United

Kingdom, measuring the differentiated impact of satisfaction (a cognitive measure), of recent well-being (an affective measure), and—uniquely in the literature—of in-the-moment well-being (also an affective measure).We combine the broad set of outcomes with the approach of focusing not only on the effect of having a baby right in the year of birth, but also on the level of well-being people report years before and years after the birth. The intention is to identify the longer-term, more comprehensive relationship between the newborn and parental well-being.

We find that compared to years two to three years before the baby, the first child is associated with decreases in satisfaction with the majority of domains of life, especially those about social life and leisure time. Meanwhile, we observe an increase in satisfaction with life overall. Recent emotions tend to be more positive after the child's arrival than before, people report higher capabilities in making difficult decisions, feeling useful, and worthwhile, especially when the child passed into toddler age and then on. Lastly, providing first evidence in the literature on the in-the-moment effect of chidren, we find that when a person is with children or does childcare or plays with children, they report consistently higher in the moment happiness and relaxation levels.

We find that overall women exhibit larger changes in well-being in these years than men do. However, our evidence is mixed for the direction of gender differences in well-being, where women are especially dissatisfied with their social life and leisure time after having kids, but are more satisfied with their health. They, similarly, first report more challenges than men do in terms of recent well-being measures in the year of pregnancy (such as enjoying activities less and being able to concentrate less), but once the child becomes a toddler, they report higher well-being. The only category where gender differences are identical across the board is in-the-moment well-being, where both being with children and doing childcare and play are associated with less happiness for women than men. This latter finding might be explained by additional analysis suggesting that time spent with children potentially more often takes the shape

of childcare for women, while more often the shaping of playing with children for men.

We suggest that our findings that children have a mixed, multifaceted effect on one's life might contribute to a more comprehensive understanding of the relationship, augmenting existing studies on the topic.

3.1 Background

The idea that costs and returns to parenthood go beyond financial ones is not new. Pollak and Wales (1979) specifically argue that monetary costs cannot be estimated only based on household consumption data alone, but need to explicitly contain information on how family members feel about the additional child. Their suggestion of appropriate welfare comparisons needing to account for feelings about the child serves as early groundwork for child-related well-being, among others, as an important variable in welfare analysis. Similarly, Wilson and Gilbert (2003) suggest that when people assess the impact of life events, what they assess is the happiness the life event brought them or took away from them, saying that "people want to be able to predict whether they will [...] have children because they believe that such life events are crucial determinants of their happiness."

In a rational choice approach people would only have children if it increases their utility more than a different allocation of income and time. That is, if they gained something, maybe happiness, from having a child that is greater than the utility or happiness they could gain using their resources otherwise. Recent longitudinal studies of parents have since offered some new perspectives on the paradoxical relationship between parenthood and well-being, however, empirical research is inconclusive. Using a nationally representative longitudinal dataset from Germany, Clark et al. (2008) show that there is a significant increase in life satisfaction for both males and females one year before and in the year of the birth of their child. They find that life satisfaction then

drops to below the prior average within one year of the newborn's arrival, and the low rates persist for the next four years, then returning to their childless satisfaction levels. The same pattern of complete hedonic adaptation to childbirth can also be found using the Australian and the British household panel datasets (Frijters et al., 2011; Clark et al., 2017). What these longitudinal studies are implying is that childbirth does indeed significantly boost overall life satisfaction for the parents, but the increase is only momentary and disappears completely within one or two years. Di Tella et al. (2003) using data from the United States, find a negative effect of children's presence for life satisfaction. Alesina et al. (2004) similarly find a substantial, negative effect on new parental happiness in America, which is especially pronounced for low income parents. Meanwhile, they find no effects in Europe, except for three children or more, which is similarly negative.

Given the clear monetary losses, one might assume that parents opt into parenthood largely due to the expected non-pecuniary gains. However, these appear to be short lived, leaving the question of why individuals still become parents. One possible explanation for this is that people often make systematic prediction errors with respect to their future utility when facing many of their life choices today (e.g. Frey and Stutzer, 2014; Kahneman and Thaler, 2006; Loewenstein et al., 2003). This is reflected in a recent study by Odermatt and Stutzer (2019) who use panel data in the setting of Germany to show that individuals tend to overestimate how satisfied or dissatisfied they will be five years into the future following the experience of either widowhood, marriage, unemployment, or disability; and by Wilson and Gilbert (2013) who show in their review study that the initial impact of a life event is mis-estimated as well as its duration.

Meanwhile, single parenting is found to be particularly detrimental to one's well-being (Frey and Stutzer, 2000). Nomaguchi and Milkie (2003), analyzing the physiological costs of becoming a parent using panel data, similarly find that single parenting

is particularly negative for self-efficacy, and comes with an increased likelihood of depression. Parenting a newborn or toddler for people in a relationship incorporates some positive and also some negative aspects, namely it increases social contacts with relatives, friends, and neighbors, but reduces the sense of freedom and goal achievement. They also note substantial gender differences: new mothers' mental well-being differs in various ways from that of childless women, such as with mentions of increased housework and marital conflict, but also a decrease in depression. Meanwhile, new fathers seem to be largely unaffected by the newborn, since their results are comparable to those of childless men.

Looking at the number of children, Clark and Oswald (2002) find that parents with one or two children are as happy as childless adults, but introducing a third child and further ones comes with a negative effect. As an opposing result, Kohler et al. (2005), using Danish data, find that for women the first child is associated with increased happiness, while the second and third each brings unhappiness, a total of four children moves the woman back to the happiness level of childless counterparts. Meanwhile, fathers are largely unaffected by each new child. They also note that fathers in particular are happier if the first-born is a boy as opposed to a girl.

On the contrary, Haller and Hadler (2006) using cross-sectional data from the World Values Survey find a positive effect of children on life satisfaction, and no effect on happiness. Some other findings are largely in line with this: Lelkes (2006) finds a positive effect of children in the home for life satisfaction using cross-sectional data from 21 European countries. McLanahan and Adams (1987), reviewing various studies from the 1970s and 1980s, largely find the contrary. They conclude that parents are less happy and less satisfied with their lives, while they also have higher levels of anxiety and depression. Dolan et al. (2011) in an Office for National Statistics publication intended to inform public policy about findings of the economics of well-being conclude that children are detrimental to life satisfaction, have no effect on momentary happiness,

while they don't find evidence either way for worthwhileness. As we can see, and as Dolan et al. (2008) note, reviewing recent research, the overall findings are mixed.

Peasgood (2008), in her doctoral thesis using British data, finds that parents score higher on the positive items of the General Health Questionnaire (GHQ), while lower on the negative ones, concluding that parenting seemingly comes with intensified positive and negative feelings. Meanwhile, she finds predominantly negative effects of the existence of children on domain satisfaction. Her findings are a good indicator of how simply looking at the relationship between overall satisfaction and children might mask a complex relationship, where children are associated differently with differing measures.

Most studies do not address the question of satisfaction by sections (or domains) of life in relation to children, rather focus only on overall life satisfaction and happiness. One exception from this is marital satisfaction, which has been studied extensively. As Twenge et al. (2003) note in a meta-analysis, pooling together a large mix of cross-sectional and panel studies predominantly from the 1970s and 1980s, parents have significantly lower marital satisfaction than non-parents, and that is especially so for mothers. They also find that women were more strongly affected, since mothers' marital satisfaction was lower than fathers'. Infants also had a stronger negative impact on marital satisfaction than older children, in particular for women's marital satisfaction. They argue that this marital dissatisfaction is due to new limits on freedom with the arrival of the baby.

There is little evidence on the impact of the presence of children on well-being in the moment, how much being with them changes one's momentary well-being. Kahneman et al. (2004) argue using the Day Reconstruction Method that time spent with childcare is unenjoyable, to a similar degree as other household tasks. On the contrary, Juster (1985) finds that doing childcare is the most desirable activity among adults, though the author suggests that the "social desirability of activities" might have impacted the results, which Kahneman et al. (2004) also argues as an explanation for the discrepancy

between their results and research prior. Kahneman et al. (2004) suggest that it might be the case that when people are asked about their feelings about spending time with their children there can be a bias to recall the more positive instances, as well a bias to give a more socially appropriate answer, while using measures in-the-moment would substantively decrease both of these possible problems.

Our study, considering among its outcomes both cognitive and affective measures in relation to parenting, is possibly closest to that of Nelson et al. (2013), who assess the impact of parenthood on life satisfaction and momentary well-being, and find that both happiness and life satisfaction are the same for parents and non-parents, using parents with children of any age, including adult children. Beyond the pooled child age, the study has some further limitations: their outcomes on life satisfaction use a cross-sectional survey, while their results on momentary well-being have a low sample size that is pooled from a wide variety of collection methods (including Amazon Mechanical Turk, face-to-face interviews with people approached in public spaces, and interviews with parents at local schools), and are based on the creation two composite indices of positive and of negative emotion mentions, and subtracting one from the other—meanwhile, physiological research suggests that positive and negative emotions are not two ends of one continuum, but can measure two distinct values (Diener, 2012).

3.2 Data

We take a multifaceted approach to estimating the impact of children on well-being, where we measure multiple aspects of well-being, as established by prior literature. Well-being can be divided into three categories—cognitive well-being, measured with life and life domain satisfaction; affective well-being, measured with recent happiness and other emotions; and eudaimonia, measured asking how worthwhile the individual considers their life to be (Dolan et al., 2011). In our study, we further separate affective

well-being into recent and in-the-moment measures, because research is mixed on the impact of children in particular along the lines of data coming from slightly longer term or very recent recall. (Research based on *de facto* in-the-moment information does not, to our knowledge, exists on the question; this study provides the first evidence in this regard). Meanwhile, we explore worthwhileness (and feelings about playing a useful role) in terms of recent emotions, where the results are as much affective well-being results as eudaimonic well-being results, because of data limitations.

3.2.1 British Household Panel Survey

For measuring how much having one's first child affects overall life satisfaction and its domains, as well as what role it plays in recent feelings, we use the British Household Panel Survey (BHPS). The BHPS spans 18 rounds from 1991 to 2009, and of these waves 6 to 18 (1997 to 2009) inquire about domain satisfactions. Therefore, we consider childbirths in this period. The advantage of the panel structure is that we are able to focus specifically on how when having a first child one's well-being changes, controlling for time-invariant personal characteristics. Using the BHPS, we estimate the impact of children over an exceptionally long time frame, from three years before the newborn's arrival through eight years after. We do so because the arrival of children might be one of the most extensive and long running changes in one's life, and we are interested in understanding both their immediate impact and their longer term effect.

Our variables of interest for cognitive well-being are overall life satisfaction, satisfaction with health, household income, housing, spouse, job, social life, amount of leisure time, and use of leisure time. We compare individuals' well-being levels two to three years before the arrival of their first child to the year right before, the year of, and the years following the arrival. With regard to affective (recent) well-being, we use the 12-item General Health Questionnaire (GHQ), a widely-validated measure of well-being and mental health (e.g. Hardy et al., 1999, in the English context). The questions

within the GHQ relate to: concentration, loss of sleep, sense of playing a useful role, feeling capable of making decisions, feeling under strain, problems overcoming difficulties, enjoying activities, feeling able to face problems, feeling unhappy or depressed, losing confidence, feeling worthless, and feelings of general happiness.

The identification of the first child born to the individual is not straightforward using each round individually, therefore the UK Data Service has created a consolidated lifetime history on individual fertility (Pronzato, 2011), and we apply this dataset to identify when an individual had their first child. Using the year and month of the birth of the first child, and information on the date of response for the specific individual in each survey round, we can identify between exactly which two rounds the child was born. For example, hypothetically, if a child was born in April 2000 and the individual's response date for round 8 was December 1 1999 and for round 9 it was October 1 2000, we know they had a newborn for the first time in round 9. This method ensures that births are assigned to the factual, person-specific round, which would not be the case if for example we considered every birth before September to have an impact in that year's survey round, as the individual might have responded in the given year already in August (see further information on sample criteria in Table B1 in the Appendix). The study focuses specifically on firstborns, because second and later children are possibly associated with different well-being impacts—as seen in prior literature—and we can expect adaptation to take place with additional children.

We note that our study is limited in focusing on biological children only, as the consolidated lifetime history is based on a question asking the child's date of birth only from those with a biological child. With 97.8% of children of mothers overall in the BHPS being biological (no such information is available for fathers), we capture the change around most new children in the BHPS sample, but believe a comparison of the biological children's results to well-being associations with step, foster, and adoptive children would be a promising avenue of future research in other settings.

Because both the non-monetary and the monetary costs, as well as the non-market labor associated with raising an infant, fall more heavily on women on average (Folbre, 1994), we are particularly interested in exploring whether there are any gender differences in how individuals are impacted by a newborn's arrival.

3.2.2 Mappiness

For measuring in-the-moment well-being we turn to Mappiness, a smartphone based daily-response panel dataset (MacKerron, 2012). Mappiness is unique in being able to capture the impact of day-to-day experiences using the experience sampling method, a gold standard in surveying (Kahneman et al., 2004). The Mappiness dataset consists of responses from 2010 to 2013, and it has more than 2 million responses from more than 20,000 individuals up until 2013. Of the sample, 29.3% have children. The data has been used before to answer a wide range of questions from the impact of working (Bryson and MacKerron, 2017) to that of terrorist attacks (Bryson and MacKerron, 2018). In the last decade, the use of smartphone based well-being measures, that of survey based as well as descriptive information through intelligent devices, is increasingly widely applied (Muaremi et al., 2012).

After signing up, Mappiness participants are prompted at random times every day to report on how they feel, as well as the activities they are undertaking when responding, who they are with, and whether they are indoors or outdoors. Demographic information is collected from individuals at sign-up. Using this we can identify those who have children in the household (but not the children's exact age, only that they are under 16). Further, using the questions on what activities individuals are doing at each response time and what other individuals they are with, we can identify (a) every occasion when someone is with a child, and (b) whether they are doing childcare or are playing with children.[1] These measures allow us to estimate the in-the-present impact of

[1]Each individual makes the decision as to which of 40 activities (such as working, socializing, watching TV, doing childcare and playing with children, running errands, resting, reading, doing

children—controlling for individual fixed effects—on two outcome variables: happiness and relaxation. Lastly, we can exploit the fact that it is possible to select multiple co-occurring activities to understand what circumstances usually surround childcare and play with children.

Mappiness provides information on the presence and number of children up to 16 years of age in the household. However, we lack information whether the individual has adult children (in or outside of the household), and each child's birth date. Therefore, to approximate focusing on firstborns as best as possible, we limit the sample in two ways. First, we keep in the sample only those who have exactly one child in the household. Second, we limit our sample to respondents up to age 40, hopefully avoiding misidentifying the child in the household as a firstborn for parents who might already have an adult child. (In robustness tests we also set a lower bound on age at 25, and find consistent results.) Lastly, we limit the sample of responses to those given at a time the person was not working to exclude responses from individuals whose job is childcare related.

3.2.3 Planned and unplanned child rearing

A potential challenge for the study is the lack of information in both the BHPS and Mappiness on whether the child comes from a planned or unplanned pregnancy, because average parental well-being could be substantively different in these cases. However, this concern is decreased by the fact that according to research by Frijters et al. (2011), having children shows no wellbeing-related selection effects. Using an Australian panel dataset, they find that it is only negative life events that show selection. For example, someone unhappy is more likely to get divorced or lose income, but positive events such as marriage and birth do not show such pre-event patterns.

chores, among others) they identify as doing at the time of each response, ticking all that apply. Similarly, they tick all those that apply from the individuals they are with at the time of response (such as partner, children, friends, colleagues, people one doesn't know, or being alone).

In terms of population-wide numbers, research suggests that slightly more than half (56%) of British women report their pregnancies to be planned, while 16% are unplanned, and 29% are ambivalent[2] (Wellings et al., 2013). These results suggests that while the majority of children are likely planned in the BHPS as well, a substantial minority are either not planned at all or the woman feels that the timing is "not quite right" or has "mixed feelings about the baby," leading to a mix of responses in our sample from those women having wanted and planned a baby and those who did not. In an ideal setting, we would compare planned and unplanned pregnancies; lacking such information, a possible approximation of the question could be focusing on those who are infertile—and would have desired to have a child—however, such information is not available either. Lastly, we could consider comparing the effect of biological and adoptive children, however, as noted earlier, we do not know the date of birth of adoptive children, therefore it is not possible to pursue this.

While it is true that the majority of British pregnancies are planned that does not necessarily mean that individuals know what their life with a child will look like when deciding to start a family. Wilson and Gilbert (2003) suggest that the birth of a child is one of the hardest events to predict in terms of how it will impact the individual's happiness. They argue this is so because of the lack of many prior experiences of the same event, where according to their research prediction improves with prior experience about a topic in question. This is especially true for the first child, where estimating the event's happiness impact must happen without a prototype of a similar event before, leading to what Wilson and Gilbert (2003) term the misconstrual problem, described as a situation where individuals imagine what the event will be like differently in advance than what the think of the same event during it. This fact suggests that while we are faced with the problem that most people self-select into parenthood, their self-selection

[2]The measure is a composite index of intentions, feelings about having a baby and the timing of it, and contraception use. The study is based on data from 2010 to 2012, the first time such measures are available since 1989.

does not mean that they would perfectly anticipate what parenthood will look like.

3.3 Hypotheses

We form four hypotheses based on the existing research on the relationship between children and well-being. First, we focus on domain satisfaction and satisfaction with life overall. Following findings by Clark et al. (2008), Frijters et al. (2011), and Odermatt and Stutzer (2019) we hypothesize that parenthood is immediately preceded by high satisfaction which then returns to pre-child levels after the newborn's arrival. Therefore, the hypothesis about the association between satisfaction and child rearing is as follows:

> *Hypothesis 1*: Domain and life satisfaction is high immediately before the birth year and returns to neutral, well-before-birth year levels after the birth.

Secondly, we turn to recent well-being measures. Following sometimes contradictory findings—depending on the specific variable in question (see for example Nomaguchi and Milkie, 2003; Peasgood, 2008; McLanahan and Adams, 1987)—, we hypothesize that recent well-being measures will be affected in a mixed manner. This is particularly supported by findings in Peasgood (2008), where she argues that parents score higher in positive and lower in negative GHQ measures, implying that parenthood might be characterized by more extreme, or contradictory but coexisting emotions. Therefore, the hypothesis about the association between recent well-being and child rearing is as follows:

> *Hypothesis 2*: The newborn is associated with a heightened level of both positive (such as enjoying activities) and negative (such as depression and feeling under strain) recent well-being measures.

There is little research available on momentary well-being, due to the methodological challenges associated with studying the question. Following mixed results (Kahneman et al., 2004; Juster, 1985; Dolan et al., 2011), we hypothesize the following:

Hypothesis 3: The presence of children is not associated with changes in momentary well-being.

One aspect that studies consistently report across various settings is the gender difference in the non-pecuniary costs associated with children (see for example Nomaguchi and Milkie, 2003; Nelson et al., 2013). Therefore, we hypothesize that:

Hypothesis 4: Children are more negatively associated with each of the three types of well-being outcomes for women than for men.

3.4 Empirical strategy

When estimating the impact of having a child, we use two panel datasets, which allow us to control for unobserved individual characteristics as well as response circumstances, thus allowing us to estimate the relationship between the child's presence and parental feelings.

In case of the domain satisfactions and recent well-being, we apply a fixed effects linear regression with clustered standard errors at the individual level, using the BHPS. For individual i in year t

$$WB_{it} = \alpha_i + \beta C_{it} + \gamma X_t + u_{it}$$

where WB_{it}, the dependent variable, is the measure of the k^{th} well-being outcome (domain satisfaction or GHQ measure) for individual i in year t. α_i represents the individual fixed effects, C_{it} is our key variable of interest, while γX_t captures time-varying individual characteristics, and lastly, u_{it} is the error term. C_{it} takes up 0 for responses 2 to 3 years before the newborns' arrival, and consecutive integers for t-1 (year of pregnancy), t (year of birth), t+1, t+2 to 3, t+4 to 5, and t+6 to 8; thus following the well-being association with the arrival of the child from the year of pregnancy through when the child is up to 8 years old.

The complete list of control variables (time-varying individual characteristics) are as follows: age, age squared, marital status (as a series of dummies), highest education (as a series of dummies), employment status (as a series of dummies), log of household income, home region (as a series of dummies), survey round (as a series of dummies).[3,4]

For in-the-moment happiness, relaxation, and how those change with the presence of children, we exploit the Mappiness dataset, where the estimation is as follows. For individual i at time of response t

$$H_{it} = \alpha_i + \beta C_{it} + \gamma W_t + u_{it}$$

where H_{it}, the dependent variable, is the measure of happiness or for individual i responding at time t. α_i captures the individual fixed effects, C_{it}, our variable of interest, measures the impact of children, while W_t captures the weather and circumstantial characteristics of the time and location the response arrives from, and lastly, u_{it} is the error term. The weather information controlled for at the time and location is as follows: extent of sun, cloud cover, wind speed, and if it is raining or not. Further, there is a dummy for whether it is daylight at the time and location of the response. Additionally, controls also include a set of dummies for the hour of the day, the day of the week, the month of the year, and the year, as well as for where the given response was within all the responses provided during the individual while taking part in Mappiness. Standard errors are clustered at the individual.

[3]We find that 16 responses (0.1% of the sample) are associated with an annual household income of a fraction of one pound. In these cases, we replace the log value with 0.

[4]In robustness tests we consider whether approaches fitted to address the ordinality of the dependent variable (Dickerson et al., 2014) yield similar results. Using fixed effects logit and fixed effects ordered logit models (Baetschmann et al., 2015; Hole et al., 2011)–specifically, applying the order logit method as well, because the simple logit with its need to transform the variable to become dichotomous might lead to a possible loss of statistical power, as argued by Altman and Royston (2006)–, we find consistent results. This is in line with suggestions by for example Frey and Stutzer (2000) and Ferrer-i Carbonell and Frijters (2004) who find that the linear approximation yields similar results to more complex tests in the case of well-being outcomes.

3.5 Descriptive statistics

3.5.1 British Household Panel Survey

In the BHPS, those who have their first child during the survey period–predictably–differ from those already having a child before Round 6 (from when onwards domain satisfaction data is available) and those not having a child until the survey is over. First, our new parent sample is on average at age 23 when first sampled (and 29 in the year of birth) compared to those who already have a child before the survey, where the average age is 47. Those who remain childless until the end of the survey period are the only majority male group, and are only one third as likely to be married compared to those having a child before the survey. For those who have a child during the survey marriage rates move from 17% to 58% from the first time they are surveyed to the year of birth. A similar increase in educational attainment between first and birth year is also observable, likely both of the above at least partially related to the average age change. Household sizes are quite similar across the three groups, with a predictable slight increase for those where a first baby arrives. Employment rates move in the opposing direction, where among first time parents some of those initially in full time employment move away from it, mostly into staying at home with the child in the year of birth. Lastly, household incomes grow substantially from the first survey year to birth year for the new parent sample, again likely due to an increase in age and completed education.

In the sample, average domain satisfaction is highest with regards to partner satisfaction for both men and women, which is followed by satisfaction with housing and life overall, where the rest of the domains follow closely as well (see Table B2 in the Appendix for descriptive statistics of the sample). The gender differences in average satisfaction are significant (at the 5% level) for satisfaction with health, spouse, job, social life, and amount and use of leisure time. For GHQ measures, gender differences

are significant for every variable (at the 5% level), where women report higher levels of both positive and negative recent experiences (see Table B4 in the Appendix for these results). Highest levels are reported for concentration for both genders—tied with enjoying activities for men, while for women the second highest rated category is feeling under strain. Enjoyment of activities follows third for them, while men, in reverse, report feeling under strain here.

Among the domain satisfaction and GHQ questions, all of them but that related to job and partner satisfaction were asked of every individual—job satisfaction was not asked of those not employed, and partner satisfaction was not asked of those not having a partner. Therefore, we define our sample of responses as those where a valid response is available for every domain and GHQ question, except allowing the job and partner satisfaction questions to be missing. This valid response requirement across measures only shifts the sample very slightly, from 1,795 to 1,793 respondents.

3.5.2 Mappiness

In the Mappiness dataset we observe that parents with one child in the household and individuals without children in the household differ as well, as seen in Table 3.1. Individuals with children, predictably, are slightly older, earn more, and are much more likely to be married. The respondent group of those with one child has a higher percentage of women, and has a slightly lower average number of adults in the household—possibly signify the formation of nuclear families with the child's arrival, and a move away from living with other family members or friends. (Please see further details on sample statistics in Table B3 in the Appendix.)

Table 3.1: Descriptive statistics for individuals without children and with one child in the household

	Individuals without children in the household	Individuals with one child in the household
Female	48.2%	48.9%
Age	27.9	28.4
Married	14.2%	40.7%
Number of adults in the household	2.3	2.2
Full time employed	77.9%	67.1%
Household income (£)	45,478	48,699
$N_{respondent}$	26,171	3,495

Note: Results in both columns are descriptive of the Mappiness subsample of individuals up to age 40.

3.6 Results

3.6.1 Satisfaction with domains of life

Years around the arrival of the first child are distinctively different from earlier years in various respects. As can be seen in Table 3.2, compared to the individual's self-reports when childless for 2 to 3 years more, changes are substantial in the years around the newborn's arrival. We also specifically address whether there are differences in terms of satisfaction with various domains between women and men using gender interaction terms.

We find that the largest effects are observed for social life, the amount of, and the use of leisure time satisfaction for both genders, in line with findings by Twenge et al. (2003) suggesting that newborns are associated with a new limit on freedoms. After birth, satisfaction with all three domains decline substantively (by about 15% for social life, 13% for amount of, and around 7% for use of leisure time), not recovering to pre-child levels again within the sample of up to 8 follow up years. Compared to the aforementioned effects, women endure a one and a half times as big drop as men do from giving birth to when the child is three years old. Similarly to these, income satisfaction also exhibits a negative change, largely decreasing for both genders from

Table 3.2: Domain satisfaction around the arrival of the first child

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Health	Income	House, flat	Spouse, partner	Job	Social life	Amount of leisure time	Use of leisure time	Life overall
Baseline: t-2 to 3									
t-1	0.011	-0.17***	-0.12*	0.10**	-0.020	-0.064	-0.055	-0.062	0.13***
	(0.057)	(0.065)	(0.068)	(0.049)	(0.071)	(0.056)	(0.068)	(0.063)	(0.047)
t-1 * Woman	0.27***	0.19**	-0.082	0.019	-0.037	-0.11	0.13	0.022	0.062
	(0.073)	(0.077)	(0.085)	(0.061)	(0.088)	(0.072)	(0.084)	(0.077)	(0.057)
t	0.091	-0.30***	-0.077	0.070	-0.073	-0.32***	-0.35***	-0.20**	0.13**
	(0.070)	(0.081)	(0.088)	(0.061)	(0.083)	(0.070)	(0.081)	(0.080)	(0.057)
t * Woman	0.045	0.069	-0.26***	-0.12*	0.0040	-0.28***	-0.22**	-0.10	0.053
	(0.076)	(0.082)	(0.092)	(0.066)	(0.096)	(0.077)	(0.090)	(0.084)	(0.061)
t+1	-0.077	-0.32***	-0.22**	-0.074	0.00091	-0.55***	-0.48***	-0.33***	0.011
	(0.087)	(0.10)	(0.11)	(0.076)	(0.10)	(0.085)	(0.097)	(0.099)	(0.070)
t+1 * Woman	0.16*	-0.030	-0.14	-0.11	-0.087	-0.24***	-0.29***	-0.20**	0.0055
	(0.083)	(0.085)	(0.093)	(0.072)	(0.10)	(0.082)	(0.094)	(0.089)	(0.066)
t+2 to 3	-0.11	-0.32**	-0.15	-0.035	-0.031	-0.64***	-0.55***	-0.34***	0.019
	(0.11)	(0.12)	(0.13)	(0.097)	(0.12)	(0.10)	(0.12)	(0.12)	(0.084)
t+2 to 3 * Woman	0.19**	-0.049	-0.19**	-0.15**	-0.00060	-0.11	-0.18**	-0.14*	-0.020
	(0.077)	(0.080)	(0.090)	(0.069)	(0.097)	(0.075)	(0.088)	(0.082)	(0.059)
t+4 to 5	-0.10	-0.29*	-0.24	0.015	0.083	-0.64***	-0.48***	-0.34**	0.028
	(0.14)	(0.16)	(0.16)	(0.13)	(0.16)	(0.14)	(0.15)	(0.15)	(0.11)
t+4 to 5 * Woman	0.33***	0.023	-0.019	-0.17**	-0.078	-0.12	-0.16	-0.083	0.050
	(0.088)	(0.089)	(0.097)	(0.079)	(0.11)	(0.085)	(0.098)	(0.089)	(0.068)
t+6 to 8	-0.16	-0.39*	-0.14	0.080	0.024	-0.66***	-0.46**	-0.36*	0.099
	(0.18)	(0.21)	(0.21)	(0.17)	(0.20)	(0.17)	(0.19)	(0.20)	(0.14)
t+6 to 8 * Woman	0.39***	0.071	-0.16	-0.18**	0.063	0.021	-0.089	0.066	0.0069
	(0.094)	(0.10)	(0.10)	(0.084)	(0.11)	(0.094)	(0.11)	(0.096)	(0.073)
Constant	4.45	3.08	3.42	5.11	5.95	3.62	4.45	4.55	4.16
N	11503	11503	11503	10400	9504	11503	11503	11503	11503

Sample: Those who have a first child during the survey years. Respondent N for overall life satisfaction is N=1,793.

Controls: Log of household income, age, age squared, marital status highest education, employment status, region, survey round.

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

already the year of pregnancy, by approximately 9%.

Partner satisfaction is high in the pregnancy year for both genders, while only changes for women afterward, who exhibit a drop from the year of birth persistently throughout (by around 3%). Health satisfaction only changes for women, being higher than before in every year but the year of birth (by around 5%). Housing satisfaction is lower in years around the birth, especially for women (by around 4%), while job satisfaction is largely unchanged. Lastly, overall life satisfaction is higher in the years of pregnancy and birth for both genders (by 2%), with no gender differences.

With this, we find no support for Hypothesis 1, which suggests high pre-birth levels which then return to neutral. On the contrary, we observe years immediately before birth to be mixed, while post-birth years do not return to neutral, but exhibit a persistent drop below well-before-birth years in most domains (and a persistent increase in health for women). We find more support for Hypothesis 4, women report consistently lower domain satisfaction in four domains, while a higher one in one.

As a robustness test we consider whether the association between domain satisfaction and well-being does not vary based on gender, but based on which parent is the caretaker. Using the question on who is responsible for childcare, we identify individuals who claim to be the main caretaker of children in the given response year (where the value takes up 1 for them, 0 for those who identify their partner to be the main caretaker, while those report doing so at equal rates are excluded here). Then, we label those to be caretaker individuals who report to be the main caretakers at least 75% of their response years, and identify those to be non-caretakers who report being so for at most 25% of their response years. Doing so, we could apply triple interactions with observation period, gender, and caretaker category. However, some of the cell sizes are very low, as caretaker responsibilities and gender are strongly correlated in the dataset at 0.91. In fact, we only observe 11 non-caretaker women and 17 caretaker men (these two categories together making up only 1.9% of the sample), therefore it is not possible

to interpret such triple interaction results,while a simple difference-in-difference model using caretaker-year interactions yields results very similar to those displayed.

3.6.2 Recent well-being

Table 3.3 presents the relationship between children and well-being in relation to more recent experiences. While the previous list focused on cognitive assessments of life, questions here shift the focus to recent positive and negative emotions.[5] Hardy et al. (1999), along with others in psychology and sociology, argue that each of these measures are distinct, they cannot be grouped, because they measure different underlying variables.[6] Therefore, lacking theoretical or survey design guidance on how to group the variables for discussion, we discuss the results one by one, under three broad sections: questions related to external pressures, to emotions, and to worthwhileness. Each of these variables take up values 1 through 4, where 4 is the positive outcome, so all of these are in the same direction. For example, if someone's response takes up 4 for "playing a useful role" that means they very much feel they do so. Similarly, when someone's response takes up 4 for "under strain" they do not feel to be under strain.

[5]The complete questions are as follows: (1) Have you recently been able to concentrate on whatever you are doing? (2) Have you recently lost much sleep due to some worry? (3) Have you recently felt constantly under strain? (4) Have you recently felt that you could not overcome your difficulties? (5) Have you recently been feeling unhappy and depressed? (6) Have you recently been losing confidence in yourself? (7) Have you recently been thinking of yourself as a worthless person? (8) Have you recently felt that you are playing a useful role in life? (9) Have you recently felt capable of making decisions about things? (10) Have you recently been able to enjoy your normal day-to-day activities? (11) Have you recently been able to face up to your problems? (12) Have you recently been feeling reasonably happy, all things considered?

[6]There is no conclusive research available on how they could be grouped into composite indices beyond grouping them by being a positively phrased (such as "capable of making decisions") and negatively phrased (such as "loss of sleep") (Hankins, 2008; Smith et al., 2013), which does not contribute to a better understanding of our research questions.

Table 3.3: Recent well-being around the arrival of the first child

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Concentration	Loss of sleep	Playing a useful role	Capable of decisions	Under strain	Problem overcoming difficulties	Enjoying activities	Able to face problems	Unhappy or depressed	Losing confidence	Feeling worthless	General happiness
Baseline: t-2 to 3												
t-1	-0.0026	-0.049	0.026	-0.0011	0.0036	0.033	0.020	0.0037	0.027	0.076**	-0.0034	0.094***
	(0.027)	(0.036)	(0.031)	(0.027)	(0.035)	(0.034)	(0.028)	(0.023)	(0.037)	(0.031)	(0.028)	(0.032)
t-1 * Woman	-0.072**	-0.016	-0.035	-0.042	0.078*	0.047	-0.12***	-0.040	0.11**	0.038	0.13***	0.10**
	(0.036)	(0.048)	(0.039)	(0.034)	(0.045)	(0.043)	(0.039)	(0.031)	(0.048)	(0.041)	(0.034)	(0.041)
t	-0.030	-0.00015	0.040	0.012	-0.036	0.095**	-0.023	0.00014	0.065	0.053	-0.018	0.15***
	(0.034)	(0.043)	(0.035)	(0.031)	(0.044)	(0.040)	(0.036)	(0.030)	(0.045)	(0.040)	(0.036)	(0.037)
t * Woman	-0.075*	0.047	0.100**	-0.027	0.0033	-0.039	0.0014	0.0017	0.028	-0.084*	0.078**	0.054
	(0.039)	(0.048)	(0.039)	(0.034)	(0.048)	(0.045)	(0.041)	(0.034)	(0.051)	(0.045)	(0.036)	(0.041)
t+1	0.013	-0.0058	0.010	0.023	-0.035	0.075	0.038	-0.031	-0.038	0.0072	-0.043	0.019
	(0.038)	(0.051)	(0.042)	(0.040)	(0.052)	(0.050)	(0.042)	(0.038)	(0.055)	(0.049)	(0.044)	(0.044)
t+1 * Woman	-0.030	0.049	-0.015	-0.093***	0.045	-0.0082	-0.055	-0.019	0.13**	-0.0031	0.042	0.051
	(0.038)	(0.049)	(0.038)	(0.036)	(0.049)	(0.045)	(0.042)	(0.035)	(0.052)	(0.047)	(0.040)	(0.042)
t+2 to 3	0.048	0.030	0.0070	0.029	-0.0025	0.086	0.061	-0.015	0.019	0.015	-0.027	0.084
	(0.048)	(0.062)	(0.051)	(0.050)	(0.061)	(0.062)	(0.051)	(0.047)	(0.068)	(0.062)	(0.056)	(0.055)
t+2 to 3 * Woman	-0.017	0.049	0.020	-0.051	0.014	0.0053	-0.046	-0.029	0.10**	0.035	0.056	0.0046
	(0.036)	(0.046)	(0.036)	(0.034)	(0.046)	(0.043)	(0.037)	(0.033)	(0.048)	(0.044)	(0.036)	(0.040)
t+4 to 5	0.11*	0.062	-0.0078	0.037	0.021	0.12	0.032	-0.016	0.011	0.053	-0.047	0.093
	(0.062)	(0.081)	(0.066)	(0.064)	(0.079)	(0.080)	(0.066)	(0.061)	(0.090)	(0.080)	(0.075)	(0.072)
t+4 to 5 * Woman	0.049	0.13***	0.11***	0.026	0.10**	0.077*	0.066	0.021	0.26***	0.093*	0.13***	0.063
	(0.039)	(0.049)	(0.039)	(0.036)	(0.051)	(0.046)	(0.041)	(0.035)	(0.052)	(0.047)	(0.040)	(0.043)
t+6 to 8	0.17**	0.10	0.019	0.043	0.055	0.16	0.057	-0.014	0.030	0.079	-0.016	0.14
	(0.079)	(0.10)	(0.086)	(0.084)	(0.10)	(0.10)	(0.086)	(0.078)	(0.11)	(0.10)	(0.096)	(0.091)
t+6 to 8 * Woman	0.063	0.14**	0.098**	0.025	0.094*	0.073	0.027	0.0018	0.25***	0.11**	0.13***	0.013
	(0.041)	(0.054)	(0.040)	(0.039)	(0.053)	(0.048)	(0.043)	(0.035)	(0.055)	(0.050)	(0.044)	(0.044)
Constant	2.75	2.91	3.09	3.15	3.26	3.30	3.49	3.02	2.31	2.93	3.73	2.99
N	11503	11503	11503	11503	11503	11503	11503	11503	11503	11503	11503	11503

Sample: Those who have a first child during the survey years. Respondent N for overall life satisfaction is N=1,793.

Controls: Log of household income, age, age squared, marital status highest education, employment status, region, survey round.

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Overall, recent well-being exhibits less change than satisfaction with domains of life. First, focusing on questions related to external pressures we find that not "feeling under strain" (Model 5) is only present when the child is bigger, and only for women, while a sense of not having a "problem overcoming difficulties" (Model 6) is true for both genders in the year of birth, and women when the child is 4 to 5 years old. Concentration levels (Model 1) are lower for women in the years of the pregnancy and birth, and then higher for both genders once the child reaches four years. Meanwhile, the sense of being "capable of making decisions" (Model 4) only changes right after giving birth, but here women exhibit a substantial drop. Being "able to face problems" (Model 8) is unchanged.

Next, in relation to questions related to emotions, we find still present, but somewhat weaker effects. General happiness (Model 12) is higher in the year of pregnancy and that of birth, especially so for women in the former. Reporting being "unhappy or depressed" (Model 9) and a sense of losing confidence (Model 10) substantially decrease for women (that is, their happiness and confidence increases) in the year of birth and then again from when the child is at least 4 years old. Women enjoys activities (Model 7) in the year of pregnancy less, but also "lose sleep over worry" (Model 2) less when the child is older.

The two variables related to worthwhileness, or eudaimonia are "playing a useful role" (Model 3) and "feeling worthless" (Model 11). With both of these, we find them to be unchanged in these years for men, while for women they feel to both play a more useful role and feel their life to be more worthwhile in the year of giving birth and once the child is past 4 years old.

The above results, therefore, support Hypothesis 2 (heightened level of both negative and positive emotions). We also find evidence for disputing Hypothesis 4 (women having more negative associations)—when it comes to recent measures women report more positive changes than men do.

3.6.3 In-the-moment well-being

Table 3.4: In-the-moment well-being when being with child and doing childcare, play

	(1) Happy	(2) Relaxed	(3) Happy	(4) Relaxed
With child	2.21***	0.75**		
	(0.32)	(0.35)		
With child * Woman	-1.24***	-0.94**		
	(0.41)	(0.43)		
Childcare, playing with child			4.12***	1.98***
			(0.31)	(0.33)
Childcare, playing with child * Woman			-1.60***	-1.29***
			(0.44)	(0.48)
Constant	59.5	59.4	59.5	59.4
N	137845	137845	137845	137845

All other activities and companions controlled for.
Circumstantial controls: Weather: air temperature, sunshine duration, wind speed, rain; Response given during daylight or not; Hour of the day; Day of the week; Response sequence.

In the last section of the analysis we focus on momentary well-being, using the Mappiness dataset. Here, we ask how much having a child in the household and (a) being with a child and (b) doing "childcare, playing with children" affects one's momentary well-being—happiness and relaxation. Overall, we find that children are positive for momentary well-being across the board, as seen in Table 3.4. In all of these regressions we control for each other companion option such as being along with the child also with a partner or family members or friends), as well as for each other activity option (such as along with doing childcare and play also watching TV, socializing, running errands, and so on). Doing so, we are able to for example separate the positive well-being effect of being simultaneously with a child and with one's partner, estimating the specific effect of only the former. In our specification, having controlled for companions and activities, we estimate the effect solely of being with or without the child, and doing childcare or playing with children or not.

Individuals with a child in the household report higher levels of happiness when the

child is present, but the gender differences are significant. While for men, being with a child is associated with a 3% increase in happiness and a 1% increase in relaxation, for women these changes are a 2% gain in happiness, while no change in relaxation, them reporting no different levels of relaxation when with children than when without. Similarly, men gain 6% in happiness and 3% in relaxation when doing childcare or play, while women only gain 4% and 1%, respectively. The significant gender differences we observe are less than straightforward to explain, but they might at least partially stem from the kind of activities individuals engage in with their children. For example, we find that when reporting being with children as well as doing childcare or play, women significantly more often report the co-activities of "cooking and housework," among others, while men more often report "pet care or playing with pets" and "talking and chatting." This might suggest that when reporting the activity "childcare, playing with children," women's activities could possibly be closer depicted by the first part of the expression than men's.

This result is in line with Nelson et al. (2013)'s findings, who, using the diary method, find that people report more positive feelings when they take care of children than the average of the happiness levels they report when engaging in a wide array of other activities. On the other hand, it contradicts that of Kahneman et al. (2004) who, using the Day Reconstruction Method, find that, upon recall, childcare is among the least enjoyable activities. On the contrary, we find it to be among the activities positively contributing to happiness, where it is for example as good as watching TV.

We must note that in this section we are unable to separate newborns specifically, therefore it might be possible that our momentary results differ from long term ones due to the child age, rather than the outcome measure. We can, regardless, cautiously say that based on the findings, we find support for the existence of gendered costs to parenting in line with Hypothesis 4, and we find no support for Hypothesis 3, which we have to reject, concluding that children are associated with broadly higher momentary

well-being.

3.7 Discussion

In this paper we set out to estimate the impact of the arrival of the first child on parental well-being, measured at three levels—satisfaction with domains, recent well-being, and in-the-moment well-being. Using the British Household Panel Survey dataset and the Mappiness dataset, we broadly find that children are associated with lower well-being for cognitive measures while higher for affective ones. Specifically, we reject Hypothesis 1, the proposition that domain satisfaction returns to pre-birth levels, and find that the effects are predominantly negative and persistent. With this, we also find contrary evidence to Frijters et al. (2011) and Clark et al. (2017), and we suggest that there is no complete hedonic adaptation to child rearing.

Next, we uphold Hypothesis 2, finding that newborns and small children are associated with a mix of positive and negative recent well-being changes. While we find individuals' ability to for example make decisions and feel useful increase, we also observe some negative changes—such as in being able to concentrate—, though only for women.

We reject Hypothesis 3, which suggested that being with children and doing childcare and play have no well-being benefits. On the contrary, we find both circumstances to be highly positive for both one's happiness levels and for relaxation levels.

Lastly, we uphold Hypothesis 4—which suggests women experience more negative impacts—with some reservations. We find, overall, women to report stronger associations with the presence of the newborn than men do, and these are predominantly negative in the majority of outcome categories. For domain satisfaction, they report lower levels than men do in social life, amount of leisure time, use of leisure time, and partner satisfaction, and higher levels in health. Similarly, they report lower levels

in both in-the-moment happiness and relaxation. Meanwhile, they generally report higher levels in recent well-being measures, such as feeling confident and their life to be worthwhile.

So far we have discussed the ways in which children impact parents (to be) around the years of birth. However, the well-being difference of having children might have much longer running patterns than what can be examined here. This is particularly true in parents' later life, where having children is associated with greater access to support, especially in relation to health needs (see for example Hays et al. (2003) and Grundy and Jitlal (2007) on lower levels of admission to nursing facilities among those who have children). Receiving informal care is also higher among the elderly with children. Larsson and Silverstein (2004) find that challenges with an increasing number of household activities, such as cooking, shopping, doing laundry, or house cleaning, directly impacted the level of informal care, while Grundy and Read (2012) find that mothers got increased support from their own children if facing challenges with both household activities, and with more severe limitations (such as with dressing, bathing, and eating), although this was not true for fathers. Therefore, in this last section we identify a separate BHPS sample, consisting of those 65 and above, and estimate whether they report different levels of cognitive and affective well-being than their childless counterparts in years of health shocks (such as becoming disabled or acquiring health problems). We find (in unreported results) there to be no difference between the childless elderly and those with children in how much their well-being levels are associated change in the year of a health problem. (We have no information on whether the child in fact provided any care or whether is even in contact with the respondent, which substantially limits this analysis.) Therefore, we suggest that the losses and gains up to the child turning 8 are a meaningful—though certainly not complete—portion of the child's lifetime well-being association.

3.8 Conclusion

In this paper, we provide evidence that children's impact on parental well-being is multifaceted, possibly more so than the literature was able to capture before, due to focusing on fewer outcomes. Looking at domains of satisfaction, we find that children are associated with more losses than gains, though an uptick in life satisfaction in the years of pregnancy and birth is notable.

Recent well-being measures, using the 12-item General Health Questionnaire, result in a mix of positive and negative outcomes for the years around the newborn's arrival, compared to years well before. Women report larger changes than men do, and also overall a more positive recent well-being than their counterparts. It is noteworthy that upticks in recent well-being are particularly present after the child passes 4 years of age, maybe suggesting that the gains manifest more with children requiring less constant attention, and with them spending an increasingly longer part of their day in institutional settings, such as pre-school and school.

Lastly, the presence of children at the time of the response is associated with all-around higher in-the-moment well-being, both in terms of being with children and in terms of doing childcare and playing with children. There are notable gender differences, where women report lower happiness and relaxation levels when with children and when doing childcare than men do. This, as we noted, might be related to the kind of co-activities they undertake compared to men.

Our results from the BHPS suggesting that the newborn's and small children's impact on well-being is dependent on the measure we apply might help explain the fact that results on the topic have been mixed before. Our findings are in line with Clark et al. (2008) and Frijters et al. (2011) suggesting a positive life satisfaction effect. We also find similar results to the former paper, which argues that the newborn does not persistently move the individual's life satisfaction set point However, we do find persistent changes in multiple other domains, in fact, we find this in the majority of

the nine domains. While Kohler et al. (2005) and Nelson et al. (2013) find that being a parent of a child of any age, in and out of the household, is associated with no difference in happiness and life satisfaction, we find that children in the household do bring about higher values, especially when they are present.

Based on the findings we might consider policy implications. First, the fact that both genders report strong and persistent drops in income satisfaction might suggest that even if most people anticipate children to be costly, they might not be (or can't afford to be) completely prepared to the level of costs. Information on child raising costs as well as education on saving and planning for the future financially not just in terms of purchases, such as housing, but also planning for child-related costs, might be beneficial. Similarly, with finding a substantial drop in satisfaction with social life and leisure time, especially so for women, opportunities for connecting with others could be beneficial if were to increase. Given new parents' time pressures, it is likely particularly important to make these opportunities local and easily accessible, therefore an expansion of existing parenting groups and other parent activities for example in local community centers would be worthwhile.

Overall, we contribute to the existing literature—which reports highly mixed results on the topic—with teasing out the nuances of the relationship between well-being and child rearing. We find a mix of losses and gains, and that there is no complete hedonic adaptation to becoming a parent—one's well-being is in many ways persistently altered with the arrival of their first child.

3.9 Appendix

Table B1: Definition of first births

		Round
YM of first birth < YM of interview in Round 6	Not in the sample	1
		2
		3
		4
		5
YM of interview in Round 6 < YM of first birth < YM of interview in Round 18	In the sample	6
		7
		8
		9
		10
		11
		12
		13
		14
		15
		16
		17
		18
YM of interview in Round 18 < YM of first birth	Not in the sample	No survey data

YM = year and month

Table B2: Descriptive statistics

BHPS	Response level				Individual level			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Health	5.23	1.39	1	7	5.24	1.06	1	7
Income	4.49	1.45	1	7	4.51	1.11	1	7
House, flat	5.10	1.42	1	7	5.11	1.01	1	7
Spouse, partner	6.26	1.11	1	7	6.25	0.88	1	7
Job	5.00	1.37	1	7	4.98	1.05	1	7
Social life	4.73	1.39	1	7	4.78	1.05	1	7
Amount of leisure time	4.25	1.48	1	7	4.30	1.07	1	7
Use of leisure time	4.59	1.43	1	7	4.63	1.05	1	7
Life overall	5.33	1.12	1	7	5.36	0.85	1.50	7
Concentration	2.15	0.55	1	4	2.14	0.32	1	3.67
Loss of sleep	1.89	0.77	1	4	1.89	0.53	1	4
Playing a useful role	1.92	0.54	1	4	1.91	0.31	1	3.71
Capable of decisions	1.93	0.51	1	4	1.92	0.31	1	4
Under strain	2.16	0.75	1	4	2.15	0.51	1	4
Problem overcoming difficulties	1.79	0.70	1	4	1.78	0.47	1	3.50
Enjoying activities	2.08	0.58	1	4	2.08	0.34	1	4
Able to face problems	1.99	0.49	1	4	1.98	0.28	1	3.50
Unhappy or depressed	1.85	0.82	1	4	1.84	0.56	1	3.86
Losing confidence	1.65	0.76	1	4	1.64	0.55	1	4
Feeling worthless	1.38	0.65	1	4	1.38	0.48	1	4
General happiness	1.93	0.61	1	4	1.92	0.36	1	3.57
Log of household income	10.3	0.66	0	14.0	10.3	0.54	5.79	11.9
Age	30.6	6.76	15	60	29.7	6.38	16	56.5
Marital status	2.00	1.70	1	6	2.11	1.45	1	6
Employment status	2.73	1.73	1	10	2.77	1.32	1	8.20
Highest education	5.07	2.69	1	13	5.22	2.69	1	13
Household size	3.22	1.20	1	16	3.17	0.99	1	15
Region	10.4	6.25	1	19	10.8	6.29	1	19
Survey round	13.3	3.39	6	18	13.5	2.41	6	18
$N_{response}$	11503							
$N_{respondent}$	1793							

While the oldest age we observe in the sample is 60 years old, this is because we follow parents up until children are 8 years old. The oldest age where we observe a newborn is 55, and that is for a male respondent. The oldest age where we observe a woman in the year of birth is 44.

Table B3: Descriptive statistics for the Mappiness sample

	Mean	SD	Min	Max
Happiness level	69.7	21.7	0	100
Relaxation level	67.0	23.0	0	100
With child	0.36	0.48	0	1
Childcare, playing with child	0.19	0.39	0	1
Day of the week	4.17	2.03	1	7
Hour of day (in 3 hour blocks)	14.5	4.24	0	21
Year	2010.6	0.80	2010	2013
Month	7.87	3.20	1	12
Extent of sun in response hour	0.23	0.36	0	1
Air temperature (in blocks)	9.69	5.66	0	26
Any rain in response hour	0.10	0.30	0	1
Level of visibility	2336.7	1285.1	0	7500
Wind speed	8.59	4.66	0	42
Response during daylight (dummy)	0.67	0.47	0	1
Response's order among respondent's responses (in blocks)	63.8	108.7	0	1001
$N_{response}$	137,845			
$N_{respondent}$	3,475			

Table B4: Mean well-being levels for each gender

	Complete sample	Women	Men
Domain satisfaction (Range: 1 to 7)			
Health	5.23	5.19	5.28
Income	4.49	4.43	4.55
House, flat	5.10	5.07	5.14
Spouse, partner	6.26	6.23	6.30
Job	5.00	5.01	4.99
Social life	4.73	4.71	4.75
Amount of leisure time	4.25	4.27	4.24
Use of leisure time	4.59	4.52	4.67
Life overall	5.33	5.35	5.31
Recent well-being (Range: 1 to 4)			
Concentration	2.15	2.20	2.08
Loss of sleep	1.89	1.97	1.81
Playing a useful role	1.92	1.94	1.90
Capable of decisions	1.93	1.96	1.89
Under strain	2.16	2.21	2.10
Problem overcoming difficulties	1.79	1.86	1.72
Enjoying activities	2.08	2.10	2.07
Able to face problems	1.99	2.01	1.97
Unhappy or depressed	1.85	1.92	1.77
Losing confidence	1.65	1.77	1.51
Feeling worthless	1.38	1.45	1.30
General happiness	1.93	1.94	1.93
$N_{response}$	11,503	6,197	5,306
$N_{respondent}$	1,793	963	830
Momentary well-being (Range: 0 to 100)			
Happy	69.66	69.17	70.19
Relaxed	66.97	66.69	67.28
$N_{response}$	137,845	71,471	66,374
$N_{respondent}$	3,475	1,709	1,766

The complete response sample size for spouse and partner satisfaction is 10,400, while N_{women}=5,408 and N_{men}=4,992. The complete response sample size for job satisfaction is 9,504, while N_{women}=4,579 and N_{men}=4,925.

Chapter 4

Stress on the sidewalk: The mental health costs of close proximity crime

4.1 Introduction

The true cost of crime for society is immense, yet we lack a thorough understanding of it, especially in relation to that of costs for individuals in general, beyond the victim. A crucial part of these costs is the impact of crime on how people feel in their own neighborhoods, whether criminal acts increase the local public's stress level. Becker (1968) argues that accounting only for costs associated with prevention and punishment "may be a significant understatement of the net damages to society, [...] because much of the damage is omitted." Indeed, crime has an effect beyond that on the victim, with crime levels influencing choices from home ownership, to work hours, and to physical health choices, like exercising (Hamermesh, 1999; Tita et al., 2006; Janke et al., 2016). However, we know less about how the presence of crime affects on individuals' mental health, what crime's beyond-victim mental health costs are.

This paper examines the impact of local violent criminal acts' on stress levels for those in the vicinity; for the first time in the crime and mental health literature separat-

ing the impact of stress induced by neighborhood characteristics (such as how safe the area generally appears) and that of a recent violent or sexual crime occurring nearby. Merging granular micro level, spatial data on daily crime with a daily response panel dataset on stress over a period of 8 years (2010-2017) for the United Kingdom region of Thames Valley, I find that recent violent crimes increase individual stress by approximately 3.4%; 1/4 of the size of the short term stress increase induced by the 2011 English riots, the largest violent public disturbance in the United Kingdom in decades.

The paper's contribution is threefold. First, exploiting the spatial and temporal detail in both the crime and the stress dataset (where there is information on both variables down to the date and the exact neighborhood—the latter at an area size one twentieth the size of a US zip code), this is the first paper to show the effect of individual crime events in the case of "common", non-irregular crimes. Existing research addresses the impact of extreme crimes, such as terrorist events, but not the impact of each individual crime in the case of "regular" crimes, even though these are what most individuals are frequently exposed to. In fact, well above 99.9% of all crimes are not terrorist attacks, therefore the current paper addressing "regular" crimes contributes to the understanding of the relationship between crime and stress in a context that is both overwhelmingly more typical and yet much less studied to date.

Secondly, the paper, due to its more precise estimation, is the first to inform on the dissipation of the effect of common crimes on mental health, providing results that are proportionally in line with findings from studies estimating how long the impact of extreme crimes reverberate. Thirdly, the paper considers crime levels at the specific location of the survey participant's response (using the smartphone's GPS), not only around their home, and finds that crime levels matter for the individual at a multitude of locations. This latter finding can have significant policy implications when for example considering the city-wide impact of crime-heavy locations.

Stress, "an adverse reaction due to pressure" (Office for National Statistics, 2015),

is a major contributor to productivity loss. In 2016/17, in the UK 12.5 million work days were lost due to work-related stress, which accounts for 49% of all lost work days (Health and Safety Executive, 2017). Of those who took out incapacity benefits, 38% did so due to a mental disorder, the single highest category among all medical conditions (Layard, 2005). Stress is also a substantial contributor to ill health, where increased stress can increase the odds of obesity (Cnop et al., 2012) and of heart attack both for those with and without predisposing conditions (Wilbert-Lampen et al., 2008), with even regular, non-extreme, "day-to-day stress, including environmental factors" can lead to depression (Herane-Vives et al., 2018). There is a limited understanding of how environmental factors contribute to the onset of stress in the economics literature due to the lack of high frequency panel data on stress. This research bridges that gap, using a daily response panel dataset Mappiness (MacKerron, 2012) to estimate the impact of crime on individual stress. Using crime reports over 8 years from the Thames Valley region of England, an area immediately west of London with a population of 2.1 million, I observe that crimes, specifically violent and sexual crimes, are a significant negative externality for stress.

When focusing on the temporal pattern in which violent crime impacts stress, I find the presence of a two to three day lag in the effect of crime manifesting in stress levels, where crimes two to three days prior to the response given drive the results. This implies the possibility of a mediator of the information about the crime event. Exploring the possible mediating channel of the media, I scrape leading British news sites and find that front page articles written on the topic of crime in the domestic news section have a significant impact on stress levels across the UK. Overall, the study measures the effect of each violent or sexual crime on stress, finding a significant increase in stress for those nearby these crimes, and further confirming that one channel of the effect through which crime affects stress levels is news written on crime occurring in the media.

4.2 Background

Crime is a major negative externality in contemporary societies. In Becker's (1968) seminal work, the social loss L generated by crime is defined as the sum of multiple components: the total social harm caused by the crimes, the gain to offenders, the cost of combating, and the cost of punishing the offenses[1]. The total social harm, *H(O)*, is traditionally measured as preliminarily a monetary function, such as the lost revenue from taxes in money laundering or lost productivity for a victim temporarily out of work due to a crime. For example, the social loss generated by violent crimes—estimated at 7.7% of GDP —is currently calculated by summing up costs associated with policing, the justice and the prison system, and direct damage due to the crimes committed (Institute for Economics & Peace, 2013). However, this measure is incomplete, and the current paper sets out to contribute to informing *H(O)* through measuring the stress costs due to crime.

The current paper contributes to the broad pool of works on neighborhood effects on economic and mental well-being (Katz et al., 2001; Kling et al., 2007; Ludwig et al., 2012) through the estimation of the mental health effect of local crime. As one of the early contributors to this strand of literature, looking at work as an outcome, Hamermesh (1999) finds that violent crime, and in particular homicide, leads to reduced work, especially on evenings and weekends. The impact of violent crime rates is present in macro level economic indicators too. It has an adverse effect on business activity (Greenbaum and Tita, 2004), on house prices (Tita et al., 2006), and on income inequality (Rufrancos et al., 2013). Similarly, high rates of violent crime also have adverse physical health effects. Janke et al. (2016) show, using British data, that violent

[1]In Becker's work the total loss function L of crime is as follows:

$$L = H(O) - G(O) + C(p,\ O) + bpfO$$

where *H(O)* is the extent of harm by the number of offenses, G(O) is the gain to offenders by the number of offenses, *C(p, O)* is the cost of combating O offenses with p probability of conviction, and *bpfO* is the total social loss from punishment (a multiplication of *bf*, the loss per offense, and *pO*, the number of offenses punished).

crime leads to a reduction in walking and exercising in one's home neighborhood, while Messer et al. (2006) found in the US context that it leads to pre-term births and lower birth rates. Research on the mental health effects of crime is limited, though Cornaglia et al. (2014) using data on Australia show that this type of crime leads to a reduction in physiological well-being. This study uses a composite index, however, which is a combination of 12 questions on mental (and sometimes physical) functioning; and the decomposition suggests that crime's effect on well-being is mostly driven by a reduction in "engagement in social and other daily activities due to the individual's physical or mental health," but it is unclear whether the channel of effect is through physical health, mental health, or the reduced activity level.

There is more evidence on the impact of exceptionally severe violent acts, such as terrorism, on mental health. Bryson and MacKerron (2018), using an event study setup, show that IRA bombings that lead to death significantly increase stress and anxiety among the population in Northern Ireland, and Metcalfe et al. (2011) provide evidence that the September 11th attacks in the United States even affected the British population's well-being.

Opposing this strand of findings are papers suggesting that the beyond-victim costs are predominantly driven by property crimes. Here, Gibbons (2004), writing specifically about London, and opposing Greenbaum and Tita (2004)'s findings, suggests that an increase in property crime leads to property prices dropping, driven specifically by criminal damage. In his interpretation, it is perception of crime through graffiti and vandalism that leads to a higher fear of crime, which then reflects in property prices. Meanwhile, Dustmann and Fasani (2016) find that high property crime rates significantly increase residential anxiety and depression.

The present paper advances the scarce, existing literature on the mental health effect of crime in a unique combination of data with temporal and spatial precision, and with the more precise definition of the outcome variable. Studies by Cornaglia et al.

(2014) and Dustmann and Fasani (2016), the two papers closest to the present study, both use annual surveys for measuring well-being, and annual and quarterly data on crime, respectively. Additionally, crime is measured at a larger regional or city level, specifically at the Local Government Area (in Australia) and at the Local Authority (in the UK) levels, which have an average of 215,000 and 145,000 residents. In comparison to those papers, the current paper measures crime at an area level which has an average of 250 adult residents. Lastly, both aforementioned papers measure their dependent variable as a composite index—one reaching key significance on a variable mixing physical and mental health and the other pooling together anxiety and depression, two quite different mental health conditions—thus hindering the precise understanding of how human well-being is impacted. This paper, on the other hand, uses a single, more straightforwardly interpretable, measure of stress over a composite index.

While there is a growing amount of work on the effect of neighborhood-level circumstances on sexual crimes (see for example Blanes i Vidal et al. (2017) on domestic abuse specifically), there is little work on how sexual offenses specifically impact non-victims. This might be due to a combination of the factors that sexual offenses occur less regularly than other kinds of violence overall, have an outstandingly low reporting rate, and have low perpetrator conviction rates due to insufficient evidence. Sexual offender data are public in the United States, and by making use of that information, Linden and Rockoff (2008) show that house prices fall when convicted sexual offenders are present in the area. The current study contributes to research on sexual crimes by considering non-sexual, violence against the person crimes, as well as sexual crimes, in order to understand both. While the latter category cannot be interpreted alone because of the small sample size, the inclusion of these crimes strengthens the results, suggesting that sexual crimes generate a substantial well-being loss at the neighborhood-level.

Stress experienced by an individual can fall into multiple categories (Ingram and Luxton, 2005). First, there are extreme, one-off stressors—an individual, major life

event, such as being in a car accident or the loss of a loved one. Second, there are individual, socio-economic stressors, for example growing up in a poor setting. Thirdly, there are ongoing, daily life events as stressors. The type of stress discussed in this study falls into the third category, where repeated, but not personally experienced exposure to crime constitutes a non-extreme but regular stressor. At a biological level, when such a stressor occurs the neural, neuroendocrine, and the immune systems are activated—an adaptation of the body referred to as allostatis (McEwen, 1998). These systems can normally adapt efficiently, however, such adaptation comes with a cost (the "allostatic load") and does not occur normally if for example the systems are activated frequently or persistently. Therefore, if it is a question whether moderate-magnitude, high-frequency stressors can lead to long term consequences, on a biological level we ask whether such stressors induce significant enough stress for the body needing to adjust at the price of the allostatic load, leading to adverse outcomes for each system.

While the study of stress specifically due to extreme events has been at the focus of stress related research inquiry initially, by today there is extensive evidence to show that daily stressors also contribute substantially to a wide array of negative mental health, physical health, and other outcomes. Morales and Guerra (2006) for example find that higher scores on a composite index combining neighborhood stressors (local violent crime exposure) and family stressors (low family income and family transitions) leads to increased likelihood of depression and aggression as well as lower achievement among school aged children. Meanwhile, using a nationally representative sample in Germany, Schonfeld et al. (2016) find that daily stressors (an index combining smaller problems with family, health, dissatisfaction with one's job, housing, or difficulties with other persons) are positively correlated depression, anxiety, stress, as well as with a composite index of overall poor mental health. Almeida et al. (2002) show that daily stressors substantively correlate with negative mood using a survey tool called the Daily Inventory of Stressful Events (DISE)—a combination of questions on stress related to

daily encounters, such as concerns about work demands, public transit, neighborhood concerns, and household repairs—where Charles et al. (2013) using DISE find that those who reported higher stress on days with stressors were more likely identified with mental disorders later on. Finally, daily stressors don't only impact mental health but physical health as well. Using DISE Piazza et al. (2013) show that daily stress due to stressors also leads to higher odds of the presence of a chronic condition—especially that of digestive conditions—years later, controlling for the individual's underlying, trait-like negative affect level.

4.3 Data

4.3.1 Crime

The high-impact, personally dangerous crimes that have been on the rise in Britain are also the ones most feared by the British population. Using data from the Crime Survey for England and Wales, I find that the two types of crime respondents report an average higher than 3 (on a 1 to 4 scale) in terms of how afraid they are of from it are attacks (3.18) and rape (3.22).[2] Based on these results, I focus in the analysis on two crime categories: (1) violence against the person, which excludes sexual crimes, and (2) sexual offenses.

Publicly available data on crime are limited in their temporal and spatial specificity to a degree which would not allow the identification of the impact of each criminal event, therefore I access secure data for my analysis. Secure police data with exact location and time information is protected by each Police Force Area individually, and I access data for the Thames Valley Police Force Area due to the Force's willingness

[2]The identification of most feared crimes are author calculations using the Crime Survey for England and Wales, year 2012-13 (when they were not on the rise yet, nor was a special media attention on them). In the survey there is a series of 7 questions on fear of various types of specifically victim based crimes, such as "How worried are you about... having your home broken into and something stolen?". See further information on the Crime Survey here: http://www.crimesurvey.co.uk/en/index.html

to let academic researchers access the data securely, on-site. The force area, which has a population of 2.1 million, is directly bordered by London (Metropolitan Police). I apply crime data in my analysis for the years 2010 to 2017.

Given that I use one Police Force Area and not all of them, selection effects must be considered. Looking at its crime rate, Thames Valley ranks in the middle of all police forces in England and Wales (26^{th} of 43),[3] and its mid-way ranking in terms of crime makes the region a good fit for research providing results that can be extrapolated. In terms of geography, Thames Valley encompasses one of the biggest territories among all English and Welsh police forces, including both urban and rural areas, and in line with this, has a relatively high police workforce to population ratio, placing Thames Valley in the top quintile of forces in this regard.[4] The force area borders nine other police force areas, including London (Metropolitan Police), which consistently registers the highest crime rate in the country. The bigger cities within the jurisdiction include Oxford and Milton Keynes, as well as Slough, which sits on the eastern fringes of the area, has strong ties to London, and has well above country-average crime rates. Overall, I find Thames Valley is not an outlier among the forces in England and Wales, allowing for results that can be relevant nationally.

International trends suggest that the results can, with a cautious understanding of systematic differences, be applied elsewhere as well. For example, both in the United States and in England and Wales crime has been decreasing for the past decades, while in both countries the perception of crime is persistently higher than actual crime rates. Geographic variations are present in both, with higher crime rates generally concentrated in big cities. Furthermore, a recent trend of increases in violent crime also appears in both locations (James, 2018), though more pronounced in the United Kingdom, where compared to 2016, homicides increased by 9% (Kirchmaier and Villa Llera,

[3]See more on crime rates in police forces here: https://www.ons.gov.uk/peoplepopulationandcommunity/crimeandjustice/datasets/policeforceareadatatables

[4]See more: http://www.gov.uk/government/statistics/police-workforce-england-and-wales-31-march-2018

Kirchmaier and Villa Llera), knife crimes by 22%, and rape by 31% in 2017[5] (Office for National Statistics, 2018). In this context, estimating the total cost of social harm due to crime is particularly important.

The research makes extensive use of the fact that England has compact census geographies to a much finer level than the United States. Crime levels are measured at the so called "Output Area" level, the smallest geographical unit in the country. These areas are one twentieth of a US zip code, providing for an analysis with fine granularity. Output Areas (OA) contain an average of only 131 households (approximately 250 adults), making them the very direct area around an individual, often the size of a street (see the Appendix for a visual example of two OAs in Oxford, one of the main cities in Thames Valley).

4.3.2 Stress

Stress, one of the most prevalent negative mental states, is not a mental illness itself, but measures broader ill-being that can often translate to or exacerbate illnesses. Information on stress levels are available from a daily panel dataset, Mappiness. Mappiness, a smartphone application that is freely available to download, started in 2010 and has more than 30,000 participants who have logged more than 3 million responses. Individuals are free to sign up and leave at any time, which means that the data is not representative of the population (though it can be weighted to population averages for all major demographic attributes, except for the poorest and the oldest deciles). On the other hand, the scale of the sample allows for detailed identification, and has made possible studies on well-being at finer details than feasible before (see for example Bryson and MacKerron (2017)).

[5]Reporting of crime has changed slightly in pursuit of improving on the vast underreporting, specifically in the case of some of these high-impact crimes, but the Office for National Statistics (ONS) notes that, regardless, there is an objective increase in these crimes.
Knife crimes are defined as possession of weapons offenses where the weapon was a knife or another sharp object.

Selection effects are important to consider. There are three contributing factors that support the extrapolation of the results from the dataset to a broader context. First, the application was presented as a tool to better understand one's well-being and happiness, and was targeted at the broad population (see examples of the pages of the application in the Appendix). It never used the label mental health or mental ill-being, highlighting its intention to focus on the happiness of the general population instead, using the tag line "happiness across space in the UK." The main reason for participation was to understand one's own well-being–achieved through charts provided by the app on where, with whom, and when the respondent is happiest; available after a sufficient number of responses were provided. Second, it was introduced at the height of the so called quantified self movement, leading to an immediate, high level of both media coverage and participation. The quantified self movement is the idea of tracking oneself with technology, and tools for this have proliferated in the past decade, including the Fitbit Tracker and the Apple Watch, where participants use these apps for the broad purposes of better understanding themselves and for self-improvement. In line with the popularity of the topic, but a lack of availability of self-tracking at the time for purposes beyond physical health and fitness, the application got widespread media coverage. News about the Mappiness app appeared on the BBC, the CNN, the Wall Street Journal, NPR, and The Times, among others. As a result, the app reached half its target participant number (3000 individuals) within two days of launching, only to ultimately surpass it tenfold. Third, the app was explicitly designed for scientific study only, reaching participants who would have possibly not taken part in a study if the data were to then be sold for business purposes. Overall, while the sample inevitably overrepresents some populations due to its smartphone based nature, it is likely that it successfully reached an audience beyond those mentally ill or particularly concerned about their neighborhood.[6]

[6]See more about the quantified self movement here: https://www.theguardian.com/technology/2013/mar/27/nike-fuelband-google-glass-quantified-self

Once an individual signs up, they are alerted usually twice a day at random times to report on how they're feeling; who they're with; if they're at home, at work, or elsewhere; and what of the 40 activities they're doing at the given moment.[7] The smartphone also notes the location of the response and the home location of the respondent, thus allowing for a precise estimation on the effects of the neighborhood a respondent lives in or spends their time in. The question on stress is worded, "How relaxed are you?," in order to frame the question positively. For the analysis, the values are inverted to measure stress, acknowledging that the outcome might be a combination of stress, anxiety, and worry, for example, and serves capture the "un-relaxedness" levels of the individual.

The two ends of the survey question are labeled "Not at all" and "Extremely," and individuals are presented with a sliding scale, where each pixel available on the smartphone can be the chosen value. This leads to much greater precision and values that can be treated as cardinals, as opposed to an ordinal scale most surveys are limited to using. Furthermore, because no numbers are visible when selecting a point on the scale, mean reversion is less likely to present as a methodological problem; without seeing what value the individual selects, it is substantially harder to fall back to the same point the next day. Lastly, for the analysis, the complete, pixel-based range is re-scaled to 0 to 100 for ease of interpretation.

4.3.3 Channel of effect – Media coverage on crime

Fear of crime is a major concern for people in the United Kingdom. One in four to one in five people say that it is very or fairly likely that they will become a victim of a crime in the coming year, when actual victimization rates are around one in eight people (Office for National Statistics, 2017). This difference between perception and

See more about media coverage and the academic purpose of Mappiness here: http://v1.mappiness.org.uk/news/

[7] Responses that are given more than 60 minutes after the randomized beep arrives are excluded from the analysis to effectively measure the mood and activities at prompting time.

reality is substantial and causes persistent problems for policy makers (Duffy et al., 2008), especially as there is cross-sectional evidence to suggest that fear of crime is associated with poorer mental health (Stafford et al., 2007). Along with the likelihood of becoming the victim of a crime, individuals also over-predict the prevalence of crime itself. People slightly overestimate how much crime happens in their own neighborhood and vastly overestimate how much crime occurs nationally. Based on the Crime Survey for England and Wales conducted since 2009, in the past decade, every year a majority (ranging from 57% to 84%) of residents said they thought crime has been rising in the year prior to responding, when that has not been actually true in nearly any of the years. Those who perceived local crime to be on the rise mostly credited personal experience, word of mouth, and local newspapers as sources that informed their opinion, while those who felt national crime to rise cited tabloids, TV, radio, and the Internet as their sources. It is noteworthy that the fact that concerns about crime are mediated through awareness about them suggests that any findings will likely be underestimates. This is so because complete awareness of every crime around the individual is improbable, thus the results can only capture the size of the impact at current awareness levels, not the plausibly larger effect at complete awareness.

The broad list of credited reasons for individuals' opinion above suggests that the relationship between crime and mental health might pass through various channels. First, it is likely that word of mouth is a major contributing factor, hearing for example from a household member when getting home that someone was hurt around the corner most likely increases stress. Secondly, being in visible distance to the crime happening or to the remnants of it (police cars, cordons, signs by authorities) might have an equally strong effect, albeit this might be a weaker or less consistent channel, as it is likely rarer for someone to witness a crime in person than to be told about one. Thirdly, one might learn about a crime through the news. While it would be fascinating to explore each of these channels, due to a lack of availability of data on conversations or exact routes

of individuals, I focus in this section on whether it is possible that the channel of effect between crime and stress is at least partially through mediated information.

To test whether local crime impacts social stress through news, ideally we would reach for the local newspaper of the region. However, Thames Valley does not have a regional newspaper. What is available are city papers (such as the Oxford Mail or the Milton Keynes Citizen), where results encounter sample size limitations, as well as source data limitations.[8,9] This means that I am not able to directly test how a news piece on a crime nearby mediates the impact of its occurrence. However, it is still possible to test whether news about crime in general has an impact of individuals–a second best solution to examining the importance of the specific, localized crime.

To test whether pieces on crime in general impact individuals I collect information on news articles written on the topic of crime in print in three leading daily British newspapers, *The Sun*, *Metro* and *The Guardian*. *The Sun* and *Metro* are the most widely circulated newspapers in the country, while *The Guardian* is one of the highest regarded UK dailies, having most often been named National Newspaper of the Year in the British Press Awards, as well as the only Britain-based newspaper having won a Pulitzer Prize (shared with The Washington Post) since the turn of the century. *The Sun* and *Metro* are widely considered to be a tabloids, while *The Guardian* is thought to offer more substantial writing, so these provide differing voices to test the hypothesis.[10]

Newspaper websites are not designed predominantly to be searched on a per-day basis going back years, therefore I use the Nexis database,[11] which is a leading online compilation of printed news articles collected from most large publications. Nexis is

[8]Detailed information on the specific limitations for each of the nine local city newspapers–making them unfitting for the study–is available from the author. Such limitations range from a lack of information on whether the piece was published in the news section to a lack of clarity on the exact publication date, among others.

[9]An analysis of radio channels is not feasible for the same reason, transcribed or systematically searchable radio outlets are not available.

[10]See more on circulation and awards at these websites: https://www.abc.org.uk/report/newsbrands; www.pressawards.org.uk; https://www.pulitzer.org/prize-winners-by-category/204

[11]https://www.nexis.com

searchable by date, and the search methods are identical for all news outlets, therefore making it a better candidate for obtaining information on the population of articles on crime than individual publication websites would be. Nexis also categorizes the printed articles based on whether they were in the news section or other sections. Making use of this, I limit my search to news articles to avoid false positives, such as reviews of films premiering with violent themes in them. In the case of *The Guardian*, domestic and foreign news are also differentiated,[12] and I only keep news articles on domestic crimes. In the case of *The Sun* and *Metro* this domestic-foreign distinction is not available, but I do find the vast majority of articles written on crime occurring within the UK borders.

To identify the articles about crime in an outlet on a date, I apply a searching method called indexing. Indexing associates topics with each article in the database based on the words used in it.[13] Thus, indexing can search for a concept and find all articles that belong to this concept.[14] Nexis is ideal for identifying articles about crime events. However, it has severe limitations on the amount of data downloadable with one query. Therefore, I opt to automate the process through webscraping. Using the scraper tool Kantu, I define my search query and access and download the list of articles on crime each month for each newspaper. Each month's CSV file contains information on the date the article was published, the author, the title, the page it was published on, the length in words, and the section it was published in. Due to a change in how the articles are listed and categorized for *The Sun* in Nexis in October 2012, I limit this section of the analysis to the first half of my period only, from 2010 to September 2012 for all three newspapers to maintain comparability.

[12]The Guardian is the national newspaper with the highest circulation for which Nexis provides this distinction.

[13] An alternative method like searching articles explicitly for a keyword, for example 'crime', would not accurately locate articles about criminal offenses unless the word 'crime' happens to appear in the text of the article.

[14]According to Nexis' information provided to the author the association of articles with topics was initially created through machine learning and natural language processing, and now all incoming articles are indexed based on the preexisting data.

4.4 Empirical strategy

My estimation is based on the following simple set up. For individual i in locality l at time t

$$S_{ilt} = \beta_1 C_{l\ t-1\ to\ t-3} + \beta_2 W_{lt} + \alpha_i + \gamma_l + \delta_t + u_{ilt}$$

where S_{ilt} is the level of stress, $C_{l\ t-1\ to\ t-3}$ measures the presence of crime in the most recent three days before the response, W_{lt} captures the weather characteristics of the locality-time, α_i is the individual fixed effect, γ_l is the location fixed effect, and δ_t is the time fixed effect, while u_{ilt} is the error term.

The empirical approach makes use of the availability of information on the location of not only the respondent's home, but various other locations they spend time in or pass through. With 54.2% of responses given while the person is within their home (and a further small portion, 0.4% from the home LSOA, but not at home), the crime rate of the home neighborhood is heavily weighted in the specification. But instead of treating it as the single influential variable, as often is the case in the literature, this setup allows for a more refined estimation.

Weather and population characteristics W_{lt} are air temperature, sunlight, rain, cloud cover, and wind speed, available through the MET Office's Integrated Data Archive System (MIDAS) Land and Marine Surface Stations Data, and are based on most recent hour or most recent day estimates from the nearest or nearest three measurement towers.[15] Daylight information is from R's *StreamMetabolism* package. Furthermore, I include the annual total population for each OA as a control. Lastly, I apply both two-way fixed effects and two-way clustering of the standard errors, in both cases at the level of the individual and at the OA. Two-way fixed effects control for the innate characteristics of both the individual and the area (for example, that it's generally a stressful location or not), while the use of two-way clustered standard errors acknowledges the

[15] http://catalogue.ceda.ac.uk/uuid/220a65615218d5c9cc9e4785a3234bd0

fact that some individuals provide more responses than others and some locations have more responses coming than others.

4.5 Descriptive statistics

4.5.1 Crime

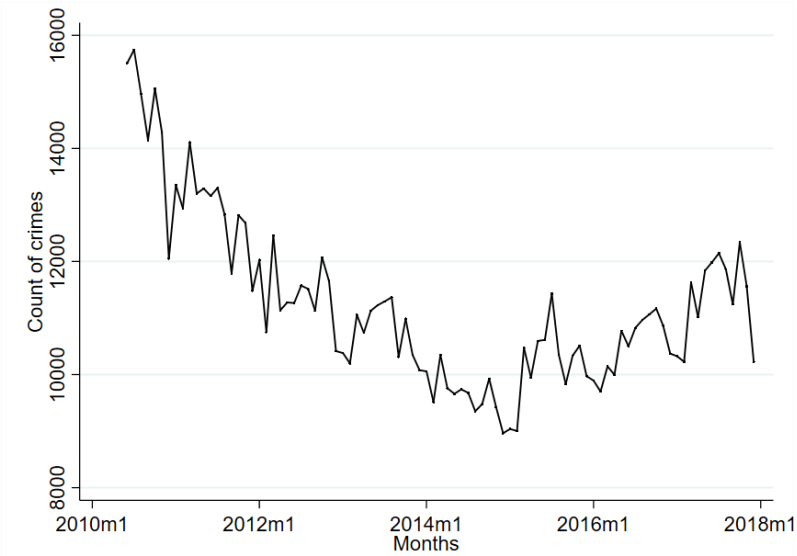
The dataset provided by Thames Valley Police contains information on each criminal offense reported to the police force, with data on the location, time, and type of the crime. Over the nearly eight years the crime data overlaps with the availability of the Mappiness data (June 2010 to December 2017), there were 1,023,841 reported crimes in Thames Valley.

Over time, the average number of crimes per year in the region was between 120,000 and 180,000, following the international trend of higher crime levels in cities and other densely populated areas, and with no part of Thames Valley being completely devoid of crime (see Figure C2 in the Appendix for the spatial distribution of crime in the region). Looking at Figure 4.1, we can observe the temporal cyclicality of crime, where summers have higher rates of crime and there is an overall downward trend in total crime over the decade, just like in the rest of the country. In the analysis, these trends are controlled for using a set of temporal controls: year (8 dummies), month (12 dummies), day of the week (7 dummies), hour of the day (8 dummies, for each 3 hour block of the day), and daylight or nighttime (1 dummy, which is based on the time of sunset on the date and exact location of the response) are included in all regressions as variables.

The police forces in England and Wales use a nested system for categorizing crime, which is often referred to as a crime tree.[16] All crimes are categorized into two broad categories, victim based crimes and non-victim based offenses. In the second level of categorization, nine categorizes are differentiated. Victim based crimes include violence

[16]See more about the crime tree here:
https://www.justiceinspectorates.gov.uk/hmicfrs/crime-and-policing-comparator/about-the-data/

Figure 4.1: Distribution of monthly crime rates in Thames Valley – June 2010 - December 2017



against the person, sexual offenses, robbery, theft and burglary, and arson and criminal damage. Non-victim based crimes include drug offenses, weapons offenses, public order offenses, and miscellaneous crimes.

The two kinds of offenses this research focuses on comprise 20.48% of crimes, with violence against the person constituting 18.22% of all crimes, and sexual offenses 2.26% (see Table 4.1 for the crime tree with a focus on these crimes, as well as Table C1 in the Appendix for a complete crime tree for all crimes). Violence against the person encompasses a wide range of illegal activities from assault to stalking to child abduction. The most often reported violent crimes are assault without injury, assault occasioning actual bodily harm, common assault and battery, and harassment.[17] Sexual offenses are rapes in 31% of the cases, while the remaining 69% include categories such as administering a substance with intent (to commit a sexual offence), attempted rape, and exposure. Non violent and non sexual crimes are used in the estimation as the base

[17]Further violent crimes that occurred in more than 1000 cases during the observation period: Threats to kill, assault (with injury) on constable, breach of restraining order, owner or person in charge allowing dog to be dangerously out of control injuring any person or assistance dog, sending letters etc. with intent to cause distress or anxiety, wound or inflict grievous bodily harm with or without weapon, wounding with intent to do grievous bodily harm.

group.

Table 4.1: Crime tree for violent and sexual crimes reported in Thames Valley (June 2010 to December 2017)

	Freq.	%		Freq.	%
Violence Against the Person	185183	18.22	Homicide	131	0.01
			Violence with Injury	77336	7.61
			Violence without Injury	107716	10.6
Sexual Offences	22941	2.26	Rape	7067	0.7
			Other Sexual Offences	15874	1.56
Robbery	9440	0.93			
Theft Offences	550814	54.2			
Criminal Damage and Arson Offence	143369	14.11			
Drug Offences	44986	4.43			
Possession of Weapons Offences	6601	0.65			
Public Order Offences	38771	3.81			
Miscellaneous Crimes Against Society	14246	1.4			
Total	1,016,351				

When a crime is reported, the category it falls into is always determined by what the most severe aspect of the crime was. Furthermore, if both a victim based and a victimless crime with equal severity occurs, the incident is recorded with the victim based crime taking precedence. For example, if a person commits a violent act with injury using an illegal object, both violence against the person as well as possession of weapons offenses are present, and thus the crime will be categorized as a violence with injury crime, as that is the more severe of the two.[18]

Spatial vicinity is defined based on OAs over using exact distance from the respondent to the crime, because OAs are designated to be "constrained by obvious boundaries such as major roads," have similar population sizes, have "approximately regular shapes," be exclusively urban or exclusively rural, and be "as socially homogenous as possible based on tenure of household and dwelling type." The ways that OAs are de-

[18]See more on categorization of crimes in Crime Recording General Rules, Section F, The Principal Crime Rule. https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/721595/count-general-jul-2018.pdf

lineated prove advantageous for this research, as crimes are more likely to be perceived to be in the neighborhood or be nearby in areas that have a sense of unity based on various types of borders, rather than in areas strictly defined by exact distance from a crime, which ignores these aspects. [19] There are 7,262 OAs in Thames Valley, with an average 17.73 crimes per year in each. Looking at the median annual crime level, which was 9.88 crimes per year per OA, it is clear that the distribution of crime in OAs is heavily left skewed (see figure in Appendix). The average number of crimes per day in the whole of Thames Valley is 378, which translates to an average of 0.04 crimes per day per OA. This means that, on average on any given street every month, one reported crime happens. At the OA, using the initial dataset of offense lists, a daily crime level is then calculated for violent and sexual crimes, as well as for all other crimes together.

When controlling for neighborhood characteristics, this paper also uses the area level of Lower Layer Super Output Area (LSOA). Thames Valley has 1,423 LSOAs, which have an average of 1,614 residents and take up only a neighborhood in a small town, or a tiny village. OAs are one-fifth the size of an LSOA. Using area fixed effects first at the larger then at the smaller area level allows for identifying in what vicinity crime has an impact.

4.5.2 Stress

Over the observed period, 5.25%, or 100,594, of all Mappiness responses come from Thames Valley and represent 5,033 individuals. Of those responses, 75,996 come from 1,476 individuals living in Thames Valley as well (see Appendix for a detailed table as well as Figure C5 for the spatial distribution of responses).[20] Responses by individuals both living in and responding from Thames Valley form my main sample, to ensure

[19] See more on how OA borders are designed here:
https://www.ons.gov.uk/methodology/geography/ukgeographies/censusgeography#output-area-oa

[20] Most individuals cross administrative borders with some frequency, that is why we see three times as many respondents who responded from Thames Valley at least twice, but don't live there, than those who live there. Similarly, those living in Thames Valley gave 83.7% of their responses within it, and 16.3% outside of it.

that we observe crime levels at the majority of their responses.[21]

Among responses given within Thames Valley, 52.7% were responses coming from an area that had some crime reported in the previous two weeks. In terms of individuals, 79.5% of respondents responded at least once in an area where some crime happened in the past two weeks, suggesting that most people regularly spend time in areas where crime has happened. If we look only at the day before the response, 12.6% of responses came from streets with one crime and 4.7% with more than one crime reported the day before (see Appendix).

The sample of Mappiness respondents within Thames Valley—as countrywide as well—are different in some aspects to the population average. In particular, respondents are financially better off, younger, and more likely to be employed than the average resident. On the other hand, the gender and the average household size are similar to the population overall (see Appendix for tabulated information on the demographic characteristics).

4.5.3 Media coverage on crime

Crime is a very actively discussed topic in each of the three publications, with the majority of dates indeed having at least one article on crime. Between 2010 and September 2012 *The Sun* had 75.1% of its published issues have at least one article on the topic of crime in the news section, *Metro* had 69.3% of its issues, while *The Guardian* had 90.3%. The newspapers, respectively, had a crime related news piece on their cover page 9.3%, 29.2%, and 19.8% of the dates.

[21] The results are robust to sample selection, where when using an expanded sample of all responses, both from those living in and those living outside of Thames Valley, I find the estimates to be consistent.

4.6 Results

4.6.1 Violent and sexual crimes' effect on stress

Table 4.2 displays the impact of crime in the proximity on stress with an increasing extensive set of control variables. The dependent variable is the individual's stress level measured on a 0 to 100 scale, while the key independent variable is a dummy variable measuring if there was at least one violent or sexual crime in the past three days in the OA the respondent is in at the time of the response (detailed descriptive statistics for the dependent, the independent variables, as well as all controls contained in the regression are available in Table C5 in the Appendix). Model (5), the preferred specification, includes fixed effects at the individual level, controls for the uniqueness of each month of each year, controls for the characteristics of the weather at the time and location of the response (including sun, rain, could cover, wind speed, and temperature), and controls for the characteristics of the time of the response (day of the week, hour of the day, daylight or night time). Furthermore, the Model also has fixed effects at the OA, controlling for the uniqueness of the street, square, or park. Using OA fixed effects controls for the characteristics of the neighborhood, and in that for the impact of generally ongoing crime on stress. With this complete set of controls (along with standard errors also being clustered two ways—at the individual and the OA), it is possible to estimate the impact of a specific crime. Doing so, I find that violent and sexual crimes significantly increase stress by 1.089 percentage points.

How large is this effect? The average stress level is 31.92 in the sample with an overall standard deviation of 22.9 and a within person standard deviation of 17.89. The point estimate on stress of a recent crime being 1.089, this leads to a 3.4% increase in stress, explaining 4.8% of its overall standard deviation and 6.1% of its within person standard deviation, assuming linearity. Thus, it is a substantial effect, and also highly comparable to results from other studies, such as that by Dustmann and Fasani (2016),

Table 4.2: The effect of at least one violent or sexual crime or in the past three days

	(1)	(2)	(3)	(4)	(5)
Violent or sexual crime at t-1 to t-3	1.637*	2.316***	1.850***	0.977**	1.089***
	(0.932)	(0.495)	(0.423)	(0.395)	(0.362)
Other crime at t-1 to t-3	3.272**	2.457***	1.678***	0.0647	0.0391
	(1.327)	(0.419)	(0.337)	(0.279)	(0.290)
Individual fixed effects		Yes	Yes	Yes	Yes
Clustered standard errors		Yes	Yes	Yes	Yes
Year*Month		Yes	Yes	Yes	Yes
Circumstantial controls			Yes	Yes	Yes
LSOA fixed efects				Yes	
OA fixed effects					Yes
Constant	34.55***	44.44***	50.08***	41.97***	44.99***
	(0.751)	(4.010)	(5.576)	(6.317)	(4.325)
N	74083	74083	74083	74083	74083

Other crime: robbery, theft, criminal damage and arson, drug offences, possession of weapons, public order offences, and miscellaneous crimes

to anchor the size of the effect.

Respondent sample size in Model (5): 1379.

Regressions with the full set of controls are available from author upon request.

* p<0.10, ** p<0.05, *** p<0.01

who find that the log of the total crime rate increases a composite index (the General Health Questionnaire 12 item questions) of mental health by 2.6%, explaining 5.3% of its overall variation. Notably though, they find this to be driven by property crimes, while my results suggests that with a more complete list of controls the relationship between crime and mental health is driven by violent and sexual crimes.

Expressing the same in terms of comparisons, a recent crime in the vicinity adds as much stress for the individual as the day of the week being Monday over it being Friday. Similarly, a recent crime increases stress to a similar level as it being the peak time of rush hour and morning stress (8 to 9 am) over it being lunchtime (1 to 2 pm). Lastly, comparing the stress increase to that caused by the 2011 English riots–the largest riots in the United Kingdom in decades, which started in London and spread across much of England–I find that an immediate vicinity violent and sexual crime increased stress approximately 1/4 the level compared to the riots for those in the same (broader) neighborhood where they took place. Similarly, they had approximately the same effect as the riots going on but the individual being far from them (in a different city, of in the case of London in a different city or in another London borough) (Bencsik, 2018). Even with the riots being measured at a wider area, the fact that the two estimates are relatively close to each other suggests that while extreme violence, such as riots have a predictably larger impact, regularly occurring violent crimes in the immediate vicinity are not far behind in their effect in their direct proximity. Notably, the above is also broadly in line with findings by Dustmann and Fasani (2016) who suggest that local crime's impact on stress is about one seventh the size of the short term effect of the 2005 London Bombings for residents in major cities in the UK.[22]

[22] Interpreting the size of the coefficient in alternative ways has limited possibilities. Because of the unusually detailed geographical level, local variables—such as local unemployment rate—are not available at this granularity. Similarly, comparing the outcome to other outcomes often found in surveys—such as crime's impact on school attendance or life satisfaction—is not possible due to the nature of the stress data. An alternative path would be the expression of the coefficient in monetized terms through translating it to a dollar value. Here, again, the most typical route is to take the well-being or mental health variable in annual surveys, and assess how it changes due to a change in income, and then compute the income equivalent of the given reported health change. However, because

It is noteworthy that the significance on other crimes—that is, robbery, theft, criminal damage and arson, drug offences, possession of weapons, public order offences, and miscellaneous crimes—persists with the majority of the controls already in place (as in Model (3)), and it is the introduction of the LSOA (approximately the size a small city neighborhood, on average 5 OAs make up an LSOA) level fixed effects where other crimes become insignificant. It is thus possible that, even with the full set of prior controls the impact of how dangerous or safe the neighborhood appears in general is conflated with the effect of the recent presence of non-violent, non-sexual crimes unless very precise location controls are in place.[23] The paper thus contributes to identifying how important it is to control for the uniqueness of the locality to identify a likely causal relationship. If I further decompose violent crimes according to the third level of the crime tree–whether an injury occurred–, I find that it is likely that predominantly violent crimes with injury drive the results (see decomposition results in the Appendix in Table C6).[24] Lastly, I test whether there is heterogeneity along certain demographic characteristics of the respondents, however I find no evidence of such. Women, young people (below 25), or those on low income (earnings below £13,000 per year) do not report different levels of impact than their counterparts. This is rather surprising in particular in the case of women, who tend to report higher rates of fear of crime. One note to add here is that sexual crimes—from which in particular women tend to report higher levels of fear (Schafer and Bynum, 2006)—make up a small percentage of all crimes considered, which might contribute to the lack of heterogeneity in this regard. One possible interpretation for the lack of heterogeneity is to consider whether crimes in

Mappiness participation is highly regular but runs for a relatively short period of time compared to annual panels, there is no information on income changes that could be applied here. Similarly, I don't get to observe major life events, such as getting married or being laid off.

[23]It is also not the case that the category "other crimes" encompasses too many different types of crimes, and that heterogeneity drives the lack of significance. When the variable is re-tested using only theft offences and then only criminal damage and arson offences (the two other individual categories with high enough occurrence rate for meaningful analysis), I find results to maintain their insignificance.

[24]Violent crimes with and without injury as a crime near an individual have a broadly similar prevalence rate in my sample, with violent crime with injury being slightly more often experienced in the vicinity.

such a clear vicinity to the individual (and having controlled away the neighborhood's impact on fear of crimes) leaves an impact that is so precisely defined that at this stage is similar for most people.

Addressing the pace of dissipation, I find that the impact of crime on stress lasts three days, where crimes reported in the past three days increase stress levels, while earlier ones do not. This result is proportionally in line with findings on the impact of more severe criminal events. Metcalfe et al. (2011) find that the impact of the September 11 attacks on the well-being of the population of the United Kingdom lasted for approximately nine weeks. Meanwhile, Bor et al. (2018) find that the mental health impact of an unarmed black person being fatally shot by police on black residents in the same state (that is, an in-group both in terms of race and geography) lasts approximately six weeks. Lastly, Becker and Rubinstein (2004) find that in Israel the behavioral change of reduced use of public transport after suicide bombers on buses lasts for approximately two to three weeks. Therefore, a finding that non-extreme, more regularly occurring and less often fatal violent crime has an impact for an average of three days is reasonable based on these prior results.

It is also noteworthy that while interpretation of the treatment for the average individual is important, it is equally important to understand whether even relatively moderate stress can have lasting consequences for certain subpopulations. For example, among pregnant women Huizink et al. (2003) find that a 1 percentage point increase in the level of daily hassles (a composite index of questions pertaining to a wide range of topics from misplacing objects to traffic jams) on any given day reported by the individual during early pregnancy is associated with a 5 percentage point decrease in the mental development score of their 8 month old infant later on. To put this in perspective, the same level of change in the mental development score but in the positive direction was observed among infants who were given milk formula enhanced by docosahexaenoic acid, which is usually only found in breast milk, and has increasingly

been suggested as beneficial for infant development (Birch et al., 2000).

4.6.2 Robustness checks

These results are robust to various tests. A falsification test imputing the crime levels of 5, 15, 30, and 90 days in the future all prove insignificant, thus suggesting that the findings causally link violent and sexual crime levels to individual stress (see results in Appendix in Table C7). Next, I exclude temporally or spatially extreme crimes and find that the results are identical. In terms of temporally extreme crime, I re-run my results excluding responses from August 2011, because that month saw the largest riots in recent UK history, which spread nationwide and had their own substantial negative well-being cost (Bencsik, 2018). In terms of spatially extreme crime, I find that one particular OA has three days every year with exceptionally high crimes, because it is the site of the annual Reading Rock Festival.[25] I exclude all responses from this OA and the results hold.

Next, I test the temporal length of the effect. Regressions containing crimes separately at t-1 to t-3 and at t-4 to t-7 (and in unreported results at t-8 to t-14, and further in the past) show that it is only the past three days that have an effect, earlier crimes have no impact on stress (see Table C8 in the Appendix).

So far I have discussed crime simply as a variable present or absent, that is, crime's impact on the extensive margin. Because most location-time periods only experienced one violent or sexual crime, I have limited power to address the impact of the intensive margin, but reestimating the model now including exactly one crime and two or more crimes separately suggests that additional crimes likely also matter, though to what degree in comparison to the first can't be interpreted due to the lack of significance for the latter variable likely caused by the small sample size (see results in Table C9 in the Appendix).

[25]Of those OA-days that register more than 20 crimes between 2010 and 2017 80.5% happened at the time and site of the festival.

Next, I test whether the results are consistent if controlling for the uniqueness of each month of each year in each locality using Year * Month * Local Authority (a broader geographical area, the lowest at which the three-way fixed effect is feasible on the dataset) controls–that is whether some unique, location based one off events drive the results instead of stress, such as for example highly localized extreme weather or a large number of special elections for local governing bodies. I find these results fully consistent with my main estimation, suggesting that it is not other time-specific local anomalies that drive the results.

Another crucial question to consider is avoidance. It might be that we don't even observe some of the negative impact of crime, because the respondent—being aware of the crime—avoids (or does not take their phone out in) the location where the crime happened, and thus their higher stress levels when responding from there is not captured. To test this, I construct a variable to measure one's presence in an OA. First, I take every response the individual gave in the month the crime in question happened, and calculate the percentage of responses for each OA for the individual for the month. Say, if for example somebody responded three times to the Mappiness in December 2018, twice from home and once from work, then their home OA response rate for December 2018 is 0.66, while their work OA response rate is 0.33. Next, I do the same for the month before, November 2018 in our example. Then, I ask whether there are significant differences between each OA's month on month response rate given if there was or there was not a crime in the OA in the second month. I find that such avoidance is not present in the sample, people systematically do not go to locations with recent crimes. This has two explanations that must be added. First, most activities an individual undertakes in a day have relatively little flexibility. With approximately half of Mappiness responses coming from one's home location, and a further substantial portion from work, it is unlikely that someone would not go home or not turn up for work due to a crime. Even if we consider activities that are not mandatory, people are

reasonably rarely inclined to skip their gym class or cancel on their friends and not go to a neighborhood bar because of crime. This leads us to the second explanation, which is that the crime count encompasses all violent and sexual crimes, including instances that wouldn't necessarily induce fear to the level of avoidance. The number of homicides don't allow for a separate analysis of only them, but it is highly plausible that if only OAs with murder were considered, we would observe avoidance behavior.

Next, I look at the spatial level of the treatment. While OAs tend to be draw around natural borders, such as major roads, it is still plausible that crimes matter to the individual not only in their OA but in nearby OAs, as well. I identify all OAs adjacent to the response OA, and input the crime treatment to be positive if any violent or sexual crime occurred in the response or any of the adjacent OAs. Results (seen in Table C10 in Appendix) here are still significant, but weaker, therefore I next separate the impact of a crime in the response OA and that of one in an adjacent OA to understand the channel better. Now I find that adjacent OA crime alone does not increase stress. This implies that crime's spatial impact is geographically limited to the area defined in the main specification. (It is worth noting that we might expect much different results if we for example focused on homicides exclusively.) Lastly, to test geographic treatment level one more way, I redefine the presence of crime at the LSOA level instead of the OA level (where about five OAs tend to make up an LSOA). My results are still significant, but weaker, just as they were when combining response OAs and adjacent OAs. Last, when I raise the treatment level of MSOA (the size of a village or half of a smaller town) the results become insignificant.

Next, I test whether the sample's demographic differences from the population might be concerning, specifically, whether the respondents are unrepresentatively financially well off. I exclude those in the top 10% of the income distribution in the UK and find that the results hold up on the truncated sample. Lastly, because Doleac and Sanders (2015) show a consistent relationship between criminal activity and moving into and out

of Daylight Savings Time, I create a set of dummies for the spring and fall clock change dates and, adding these as independent variables, I find the results to be unchanged.

One question when considering individuals' re-treatment with proximate crime is whether there are long term adjustment patterns in either direction due to the exposure. For example, Di Tella et al. (2019) find in the Argentinian setting that those who were victimized before have a lower degree of both biological and cognitive reaction to watching real crime videos in a lab experiment than those not before victimized. Meanwhile, research on the long term costs of exposure to violence (Hipp, 2010) might suggest a stronger than linear pattern in the cost of violence. Answering whether repeated exposure to crime changes how much it impacts stress is beyond the scope of the paper, but a few indications are as follows. First, as noted above, second crimes in the same area during the same time likely add further stress for the individual, though sample size limitations mean this estimate is not significant. Second, I find (in unreported results) that the connection between crime and stress is more pronounced in urban areas than in rural ones, the former also having higher crime rates overall. This might imply that in locations were re-treatment is more likely (where fear of another crime happening in the future is better founded) people react more to it. However, again, sample size limitations in rural settings mean this result should be interpreted with caution. Overall, these results might suggest that the theory of desensitization is less likely to fit the data, but whether the relationship is linear or something else cannot be addressed.

4.6.3 The timing of the stress response

I decompose the temporal effect of the treatment to explore what channels might contribute to the stress effect of crime. Table C11 (in Appendix) depicts the effect of any crime during each of the past seven days, and I observe two crucial takeaways. First, that the level of crime the day before the response has no impact on stress levels. Sec-

ond, that it is crimes specifically two days before that drives the results–though any interpretations here should be taken with caution due to sample size limitations. The results combined suggest that it is crimes recently but not the day before that drive the results.

To further test the above claim, I redefine the period for which the crime level is considered, and if a Mappiness response is given past noon, the crime level of t to t-3 is considered (that is, I add the level of crime on the day of the response). If the response arrives before noon, the original t-1 to t-3 period is applied. I find results defining the treatment including response day crimes to be weaker than only including past crimes, again suggesting that there is a lag between treatment and the stress change and that it is not crimes of the last 24 hours that drive the results. This lag effect is noteworthy, because if it were crimes committed yesterday that created the effect, one could argue that the impact is (predominantly) through direct exposure either to the crime itself or to crime-related activities like police cars on the street. However, the significance coming from two days ago suggests that part of the effect comes through a non-direct channel, such as word of mouth or hearing about crimes through the news media.

4.6.4 News media as a mediator between crime and stress

The two day lag between a crime being reported and it having an effect on stress levels suggests the presence of a mediator. Word of mouth, for example, would suggest that individuals directly hear about a crime having taken place from a family member or a friend, for example upon getting home from work. This mediator would be possible to explore if we had information on for example the topics of conversation between family members, which is not possible to ascertain in the current dataset. Direct observation of crime related activities, such as seeing a crime taking place, observing police personnel or police cars actively engaging with a case, or seeing remnants of such engagement, such as the tape police uses the cordon off areas, is likely a strong channel

for those who directly interact with any of these, however the number of them to the total neighborhood population is relatively low in most cases. To explore this channel, information on the exact location of police cars parked, the exact temporal length of cordon tapes being present would be required, in short, data that is not available at such granularity. The current research is similarly limited in contributing to our understanding of digital and social media, due to much of local social media content, such as local Facebook groups not being public; as well as much of digital media being hard to collect backdating up to nearly a decade, where content might be taken down, or appended after publication.[26]

Therefore, in this final section I turn my attention to print media and empirically explore the role it plays in increasing stress levels. As Messer et al. (2006) explicitly theorize that "crimes often are well-publicized neighborhood events, making them a potentially proximate and salient form of neighborhood stress" it is promising that even if exploring one of multiple channels, it is likely to be an influential one.

One drawback of using print media analysis in the Thames Valley region is that there is no one regional newspaper, but only smaller, city papers that have scarcely and insufficiently been digitized. Therefore, due to this limitation, instead of exploring local media, I turn to national news outlets. Here, however, it is important to emphasise that the channel I am able to explore changes somewhat, whereby using national news I can identify whether national level crime related news has an impact on stress levels. The key difference here is that national news are unlikely to report an event that took place in any given respondent's immediate vicinity. In fact, focusing on national cover stories of crime identifies completely separate crimes to the near-proximity actual crimes the previous section of the study focused on, therefore I anticipate that national news won't

[26]I do observe people's activities, therefore I am able to identify those who are the most active in the sample with regards to a certain behavior–for example the top 10% of respondents in terms of the share of responses for which they reported watching TV. However, I find that those with high rates of socializing, being online, watch TV, or reading don't exhibit different stress levels to the rest of the sample, likely because all of these activities tend to largely address other topics than news consumption on recent local violent crime.

mediate local crime's effect, and the question becomes whether national crime coverage has an impact at all, and if so, does it have an additional impact beyond local actual crime, or the amount of stress crime can cause to a person is fully captured by local crime, and additional national events won't influence it further.

Looking at cover page news on crime in three national outlets in Table 4.3, I find that nationally covered crimes likely increase stress, and the impact runs completely parallel with local crime–the two neither dampening nor enhancing each other. The size of the impact of crime news on the cover of *The Sun* and *Metro* are largely similar to each other, but being approximately half the effect of local violent crime, suggesting that both the seriousness or gruesomeness of a crime (signaled by it being covered on the front page of a national outlet) as well as it's personal salience (signaled by proximity) play a role in the way crime contributes to stress, overall actual local crimes still taking precedent over crimes elsewhere, however extreme they might be. It is interesting to note that I find an effect for two out of three outlets where both of the two that show an effect are tabloids. This might suggest that the way crime is covered is also important, not just the fact it is covered at all.

Table 4.3: The stress effect of crime on the cover of national newspapers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		The Sun	The Sun	Metro	Metro	The Guardian	The Guardian
Violent or sexual crime at t-1 to t3	1.018**		1.012**		1.017**		0.874*
	(0.404)		(0.404)		(0.405)		(0.463)
other crime at t-1 to t3	-0.111		-0.111		-0.106		-0.0700
	(0.308)		(0.308)		(0.308)		(0.335)
Crime news on newspaper's cover page at t		0.577**	0.572**	0.444**	0.443**	0.0347	0.0386
		(0.265)	(0.265)	(0.198)	(0.197)	(0.221)	(0.220)
Constant	31.37***	31.44***	31.25***	31.37***	31.17***	38.78***	38.65***
	(5.299)	(5.294)	(5.306)	(5.292)	(5.304)	(6.169)	(6.173)
N	59610	59610	59610	59610	59610	50714	50714

Note: Controls defined as in Table 4.2. Model 1 is identical to the preferred specification in Table 4.2 using the limited sample. Models (2), (4), and (6) display the impact of a cover story about crime the day of the response. Models (3), (5), and (7) display the impact of both a cover story at t as well as a local violent crime at t-1 to t-3.

It is worthy to note that the presence and the total number of articles on crime in an issue (outside of the cover) has no impact on stress levels, nor do the total number of words devoted to crime in such articles—this latter measure being a more precise proxy of the presence of crime news than article count alone. Similarly, yesterday's cover

stories have no influence. Overall, these further tests suggest that proximate actual crimes are substantially more influential, but that crime news does also contribute to stress, suggesting media being a channel between crime and stress, as expected. Lastly, it is noteworthy that the finding that front page news and stress show a significant relationship is in line with research by Smolej and Kivivuori (2006) who find that reading tabloid front pages—as well as reading multiple different kinds of news outlets—is associated with higher rates of being worried about becoming a victim of violence and with avoiding certain parts of one's neighborhood.

4.7 Conclusion

Using the region of the Thames Valley Police Force Area, I apply an analysis on every crime reported between 2010 and 2017, combined with a daily response panel data on stress. The paper contributes to the existing literature in three aspects. First, connecting crime and subsequent stress outcomes at the temporal specificity of each day and the spatial specificity of the OA, I find that violent and sexual crimes significantly increase stress for those in the OA if such a crime occurred in the past 3 days. This result is the first in the literature to estimate the beyond-victim mental health cost of each individual criminal event, a type of estimation only available before for extreme events, such as terrorist attacks.

Second, the paper is able to speak to the pace of dissipation of each criminal event, finding that stress levels are impacted by crimes of up to three days ago. I compare the three day impact length with research on the impact length of extreme crimes, such as the September 11 attacks, and find that the results are proportionally in line with the size of the events. Decomposing the effect by day, I find that the results are driven by violent and sexual crimes committed two days ago, suggesting a lag between treatment and outcome. I hypothesize that this lag is due to mediators of information, such a

word of mouth or the media. To test the latter, I scrape news websites to access data on each day's print edition and find that, both for *Metro* and for *The Sun*, front page coverage of news articles on crime has a significant effect in increasing stress levels.

Thirdly, while previous studies focused on the individual's home neighborhood, I show that it is not required for someone to live in a given neighborhood, but only to be present in it, for the negative, crime induced impact to materialize. This suggests that the negative impact reaches further than assumed before, and cities with a few crime-ridden districts can have individuals otherwise residing elsewhere in the city experience stress from visiting those districts.

Recent research has highlighted how crime's externalities go well beyond procedural costs and the impact on the victim. With long-term changes like migration out of increasingly crime-heavy cities (Cullen and Levitt, 1999), slower business growth (Greenbaum and Tita, 2004) and lower birth rates in crime-heavy locales (Messer et al., 2006), neighborhood crime has various negative consequences. Meanwhile, research also shows that such short term stress spikes as those observed here can ultimately add to larger mental health costs for the individual. Overall, the present paper both adds a further puzzle piece to our understanding of crime's externalities, as well as helping understand some of the drivers of neighborhood stress.

In light of the above, lastly, the study also contributes to explicitly estimating something other research has so far argued to be likely but could not test empirically. When discussing the link between other long term outcomes and exposure to local crime Sharkey et al. (2014), for example, empirically studying local violence and school exam results create a flowchart of the impact violence, arguing that local violence impacts students first through the activation of the stress response system and through emotional responses, which then translates to immediate effects on exam performance (the specific outcome variable they study), leading to worse long term academic outcomes. Meanwhile, Shanks and Robinson (2013), for example, in a review study argues

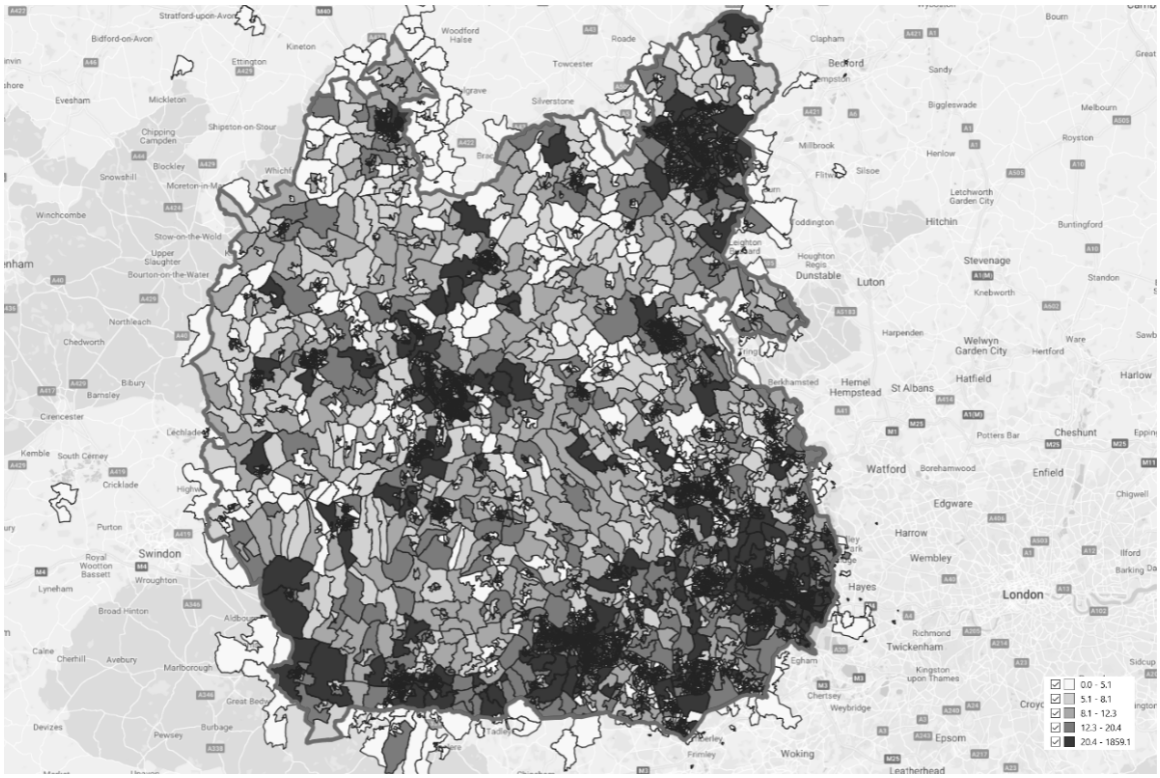
for considering stress as the mediator for a wide range of neighborhood impacts and individual outcomes. Thus, the current study causally suggesting that individual local violent crimes increase stress levels can serve us as a sign that such theories are well founded and stress might prove to be a crucial mediator between neighborhood conditions and youth and adult outcomes.

Overall, this study contributes to a more complete estimation of the social harm caused by crime and does so by focusing on stress, an outcome that then also can become a driver for additional negative effects. I conclude that the stress externality of local crime is substantive, and given the prevalence of violent and sexual crimes in most of today's societies, means an additional, repeated increase in stress for many.

4.8 Appendix

Figure C1: Example: Two Output Areas in the city of Oxford, part of Thames Valley

Figure C2: Annual average crime in each Output Area within Thames Valley



Note: OAs are based on resident size, therefore they are exceedingly small in cities, while larger in uninhibited areas, as seen on the map.
The highest crime levels - visible here as black - can be observed in cities such as Sough, Oxford, and Milton Keynes.
In a few cases OAs are mapped outside of the border of Thames Valley as well (where the border is noted with a thick line), which occurs if the Thames Valley Police Force happened to be the one attending to a crime there.

Table C1: Crime tree for crimes reported in Thames Valley (June 2010 to December 2017)

	Freq.	%		Freq.	%		Freq.	%
Victim based crimes	911747	89.71	Violence Against the Person	185183	18.22	Homicide	131	0.01
						Violence with Injury	77336	7.61
						Violence without Injury	107716	10.60
			Sexual Offences	22941	2.26	Rape	7067	0.70
						Other Sexual Offences	15874	1.56
			Robbery	9440	0.93	Robbery		
			Theft Offences	550814	54.20	Domestic Burglary	43167	4.25
						Non Domestic Burglary	55801	5.49
						Residential Burglary	6238	0.61
						Business and Community Burglary	2674	0.26
						Vehicle Offences	103923	10.23
						Theft from the Person	23459	2.31
						Bicycle Theft	42926	4.22
						Shoplifting	106082	10.44
						All Other Theft Offences	166544	16.39
			Criminal Damage and Arson Offence	143369	14.11	Criminal Damage	136753	13.46
						Arson	6616	0.65
Non victim based crimes	104604	10.29	Drug Offences	44986	4.43	Trafficking of Drugs	6156	0.61
						Possession of Drugs	38830	3.82
			Possession of Weapons Offences	6601	0.65	Possession of Weapons Offences		
			Public Order Offences	38771	3.81	Public Order Offences		
			Miscellaneous Crimes Against Society	14246	1.40	Miscellaneous Crimes Against Society		
						Total	1016351	

Table C2: Mappiness sample in Thames Valley

	Freq.	%		Freq.	%
Response not in TV	1,815,729	94.8			
Response in TV	100,594	5.25	From respondent living in TV	75,996	75.5
	(5,033)			(1,476)	
			From respondent living outside of TV	14,812	14.7
			Unknown home location	9,786	9.7
Total	1,916,323			100,594	

Respondent sample size in brackets underneath.
Home location is most often unidentified for individuals who only respond a limited number of times, and not from home, thus the identification of home location is not possible.

Table C3: Demographic characteristics of Mappiness participants and the population

	(1) Respondents who responded from TV at least once (extended sample)	(2) Respondents living in TV (main sample)	(3) Population characteristics
Female	49.1	51.8	55.9
Average age	34	34	48
Average number of adults in household	2.2	2.2	2.3
Average household income	57,963	59,075	22,375
Employed	81.6	77.7	59
Married	35.1	37.3	55.3
At least one child in household	29.2	34.8	32.3

Population characteristics are calculations by the author (except for income, see below), using the Understanding Society dataset, year 2011-2012. Police Force Areas have different geographic borders to the nested statistical geography system of England, therefore demographic characteristics are not available at a level to contain only, and just only the exact area with a PFA. PFAs are however nested within regions, therefore these statistics are available at the level to represent the whole of the South East, which contains Thames Valley, alongside with Hampshire, Kent, Surrey, and Sussex.
Household income per head for the South East available from here: https://www.ons.gov.uk/economy/regionalaccounts/ grossdisposablehouseholdincome/bulletins/ regionalgrossdisposablehouseholdincomegdhi/1997to2016

Table C4: Individual responses' exposure to crime in the response OA yesterday

	Violence	Sexual offenses	Robbery	Theft, burglary	Arson, criminal damage	Drugs	Weapons offenses	Public order offenses	Misc.
%									
No crime	97.4	99.7	99.8	91.0	98.2	99.2	99.9	98.5	99.7
1 crime	2.09	0.28	0.22	6.03	1.72	0.70	0.14	1.14	0.29
2 crimes	0.33	0.0080	0.015	1.50	0.088	0.099		0.24	0.0070
3 or more	0.14	0.0020		1.47	0.013	0.025		0.13	0.0040
Freq.									
No crime	98010	100305	100362	91539	98758	99761	100457	99070	100287
1 crime	2107	279	217	6065	1735	708	137	1147	296
2 crimes	336	8	15	1512	89	100		246	7
3 or more	141	2		1479	13	25		131	4
Total	100594	100594	100594	100595	100595	100594	100594	100594	100594

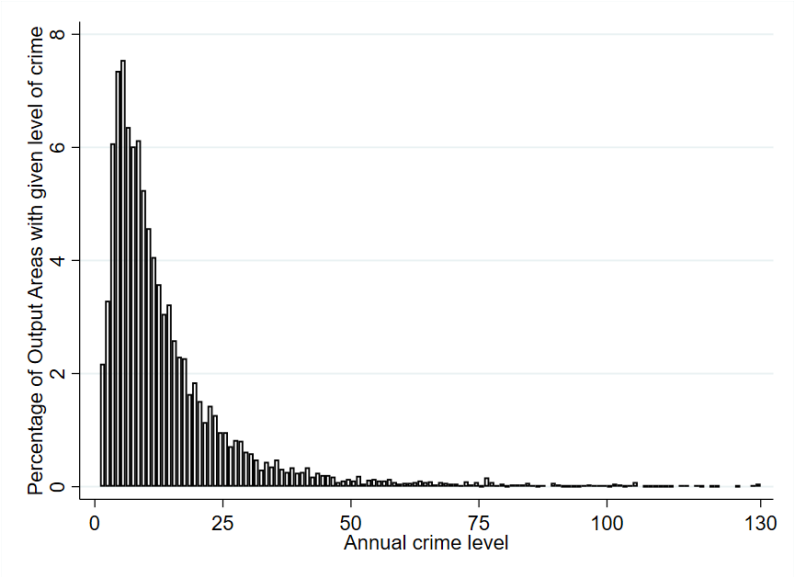
Figure C3: Screenshots of the Mappiness application

Picture 1: One of the question pages, asking to rate one's well-being. Picture 2 and 3: Feedback pages on one's own well-being, which become available after a sufficient number of responses were provided for meaningful feedback.
Source: http://v1.mappiness.org.uk/

Table C5: Descriptive statistics

	Mean	SD	Min	Max
Stress level	35.3	22.9	0	100
Violent or sexual crime in last 3 days in OA	0.063	0.24	0	1
Other crime crime in last 3 days in OA	0.20	0.40	0	1
Day of the week	4.00	2.02	1	7
Hour of day (in 3 hour blocks)	14.1	4.27	0	21
Year	2011.2	1.56	2010	2017
Month	7.33	3.50	1	12
Extent of sun in response hour	0.24	0.37	0	1
Air temperature (in blocks)	9.32	6.04	0	31
Any rain in response hour	0.091	0.29	0	1
Cloudiness	5.36	2.97	0	9
Level of visibility	2178.6	1224.6	0	7500
Wind speed	8.10	4.30	0	32
Response during daylight (dummy)	1.69	0.46	1	2
Total population in the OA in year of response	381.8	356.8	61	3951
Response's order among the respondents responses (in blocks)	108.9	210.2	0	1001
N	74083			

Figure C4: Distribution of the level of crime in Output Areas



Note: The annual average crime level in the top 1% of most crime-heavy OAs are not pictured for sensible visual representation. These 75 OAs' crime ranges from 130 to 1859, with some of the particularly high levels being due to the OA being a location where annual festivals or other mass events happen.

Figure C5: Average stress in each Output Area within Thames Valley

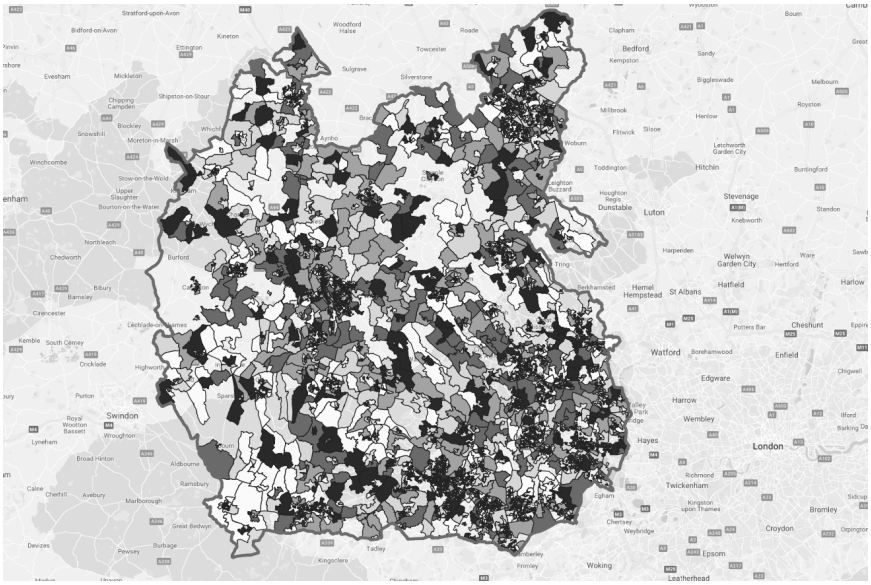


Table C6: Decomposition of violent and sexual crimes based on the presence of injury

	(1)
Violence with injury	0.865**
	(0.377)
Violence without injury	0.460
	(0.486)
Other crime	-0.00202
	(0.293)
Constant	45.06***
	(4.311)
N	74083

Note: Models defined as Table 4.2 Model (5).
Note: Sexual crimes are excluded here as there is no information provided on the presence of injury for such crimes.

Table C7: Falsification test – Future crime's impact on current stress with crime measured at 5, 15, 30, and 90 days in the future

	(1)	(2)	(3)	(4)
	5	15	30	90
Violent or sexual crime	-0.0472	-0.512	-0.0109	0.292
	(0.405)	(0.387)	(0.456)	(0.342)
Other crimes	-0.252	-0.164	-0.130	-0.0222
	(0.242)	(0.279)	(0.236)	(0.228)
Constant	44.95***	45.24***	45.12***	45.02***
	(4.307)	(4.319)	(4.312)	(4.312)
N	74083	74083	74083	74083

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table C8: Violent and sexual crime in past 1 to 3 days and 4 to 7 days

	(1)
Violent or sexual crime at t-1 to t-3	1.115***
	(0.368)
Other crime at t-1 to t-3	0.0326
	(0.290)
Violent or sexual crime at t-4 to t-7	0.512
	(0.396)
Other crime at t-4 to t-7	-0.0517
	(0.266)
Constant	45.03***
	(4.326)
N	74083

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table C9: Intensive margin effects – Levels of violent and sexual crime in past 1 to 3 days

	(1)
Violent or sexual crime at t-1 to t-3 – Count: 1	1.106***
	(0.387)
Violent or sexual crime at t-1 to t-3 – Count: 2 or more	0.986
	(0.611)
Other crime at t-1 to t-3 – Count: 1	-0.0256
	(0.317)
Other crime at t-1 to t-3 – Count: 2 or more	0.273
	(0.398)
Constant	44.94***
	(4.327)
N	74083

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table C10: Crime treatment defined at increasingly large spacial areas

	(1)	(2)	(3)	(4)
Violent or sexual crime in OA plus	0.557**			
in adjacent OA	(0.227)			
Other crime in OA plus in adjacent OA	-0.0217			
	(0.191)			
Violent or sexual crime in OA		1.082***		
		(0.362)		
Violent or sexual crime in adjacent OA		0.335		
		(0.236)		
Other crimes in OA		0.0424		
		(0.290)		
Other crimes in adjacent OA		-0.105		
		(0.193)		
Violent or sexual crime in LSOA			0.770***	
			(0.262)	
Other crimes in LSOA			-0.240	
			(0.186)	
Violent or sexual crime in MSOA				0.297
				(0.191)
Other crimes in MSOA				-0.339
				(0.303)
Constant	44.93***	44.87***	45.13***	45.32***
	(4.323)	(4.305)	(4.326)	(4.299)
N	74083	74083	74083	74083

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Table C11: Violent, sexual, and other crime in each of the past 7 days

	(1)
Violent or sexual crime at t-1	0.401
	(0.607)
Other crime at t-1	-0.456
	(0.304)
Violent or sexual crime at t-2	1.129*
	(0.591)
Other crime at t-2	-0.0254
	(0.357)
Violent or sexual crime at t-3	0.639
	(0.500)
Other crime at t-3	0.0284
	(0.301)
Violent or sexual crime at t-4	0.637
	(0.443)
Other crime at t-4	0.205
	(0.369)
Violent or sexual crime at t-5	-0.0402
	(0.582)
Other crime at t-5	-0.350
	(0.351)
Violent or sexual crime at t-6	0.465
	(0.446)
Other crime at t-6	0.198
	(0.296)
Violent or sexual crime at t-7	0.768
	(0.622)
Other crime at t-7	0.188
	(0.321)
Constant	42.21***
	(4.508)
N	74083

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Chapter 5

Conclusion

The key theme of the present thesis is a focus on the indirect financial costs and benefits of events that are either very wide-spread—such as crime and child rearing—or rare but very impactful—such as riots. The central policy-relevant question connecting the chapters of the thesis is whether well-being data can help us evaluate the non-market costs more fully. The thesis, overall, finds that it can, suggesting that well-being and mental health measures can meaningfully contribute to a more complete understanding of the topics discussed.

The first paper, analyzing the impact of riots on well-being, finds that vast majority of the country was negatively impacted with substantial costs: in areas with riots the effect size equaled the size of the effect of Christmas Eve on well-being. Limitations of this study stem predominantly from the non-representative sample used—an issue addressed in the chapter. Therefore, it would be valuable in future work to estimate the impact of extreme events with a large, nationally representative, geo-coded panel data—however, such data is not available to date.

The second paper, focusing on the arrival of the first child, finds largely negative cognitive well-being and largely positive affective well-being effects, coupled with meaningful gender differences. The finding that the type of measure applied to address the

question is strongly influential for the kind of results obtained highlights the importance of measuring well-being in a multifaceted way, and might also provide a partial explanation for why research to date has been mixed on the question. The key limitation of the study is its descriptive nature, where findings cannot be interpreted causally. As we note in the chapter, some of our findings will inevitably stem from time-varying individual characteristics, which fixed effects cannot control for, and the lack of an appropriate control group is also an issue. Consequently, a promising avenue of new research on the topic would apply quasi-experimental methods.

The third paper, applying micro-level spatial panel data, estimates the impact of violent and sexual crimes on those in the neighborhood, being the first study to do so at a crime-by-crime level in the literature. I find that individuals' stress levels increase after crimes are committed in the immediate vicinity, which suggests that every reported crime has a detrimental mental health effect, beyond that of static neighborhood characteristics. This finding implies additional social costs to crime that have not previously been precisely accounted for. Additionally, the finding that violent and sexual crimes have such a cost while other crimes do not implies that the relative cost of these two categories to other types of crime is different than it has been assumed before, which can inform policy priorities. Here, a key limitation and a promising avenue for further research is the exploration of external validity. The current study is limited in scope to Thames Valley, which while being relatively average in its crime rate, as well as containing both urban and rural areas, is not necessarily representative of the country. Therefore, a promising avenue of research would be the replication of the study in international settings. This, however, is currently hindered by data availability, but there is hope that future studies will overcome this issue, especially with the spread of smart device-based measures (such as smart watches with a heart rate monitor) and the ongoing move towards data-driven policing.

A key question when comparing the impact of the riots and of non-extreme, violent

and sexual crimes in terms of well-being and stress effects is their comparative effect size. I find that the riots induced approximately four times the size of the effect on stress as nearby local crimes did. Here, I emphasise that the effect sizes were calculated on different geographies though, where the riots' effect was measured at the Local Authority level, while local crime's was at the Output Area level. If they were measured with the same vicinity to the precise location of treatment, one would anticipate the differences to be substantially larger, which is in line with our understanding of the size of the impact of extreme versus non-extreme crime. Lastly, this comparison also provides some policy insights. The studies suggest that crime prevention, and the support for those reentering from prison are important policy goals, and with both unpredictability and vicinity being likely important drivers of the induced stress, strategies that create safer neighborhoods and support reductions in crime can be highly valuable beyond their direct crime-reducing qualities.

The research in the thesis leads to multiple possible future research streams. First, looking at the per-crime cost in the case of common crimes opens a research direction to shift focus from extreme events—which the vast majority of research in the body of literature on per-event costs focuses on—to common events when estimating costs. Moving from annual or monthly rate level analysis to an event level one has substantial advantages in informativeness and precision. Secondly, Chapter 4, which explores the impact of local crime on stress, suggests that one of the mediating factors is the news media. It was beyond the scope of the paper to identify other factors and, in particular, to understand their relative importance to one another. Therefore, a lab experiment which focuses on the importance of the channel of information between local public bads and mental health would be of great interest.

More broadly speaking, the study of mental health and well-being as economic phenomena have further potential. Intergenerational factors are strongly influential for certain physical health outcomes. However, our understanding of them in relation to

mental health is poor to date. Therefore, a study in which parent and child mental health patterns would be explored, as well as how these influence child outcomes from employment through crime to behavioral choices would be valuable. Secondly, an expansion of our understanding of how day-to-day neighborhood-level variables impact health and health choices would also be of great interest. Finding that crime impacts those beyond the victim prompts the question of how other, granularly changing neighborhood characteristics might impact health outcomes. Within such characteristics the relationship between traffic flow and health would be an interesting avenue. Building on Chapter 4, it would be particularly informative to estimate the effect of location- and date-specific traffic flow, as well as extreme traffic events (such as accidents) on health choices such as healthy eating. Similarly to local crime, if there was to be a result that relatively small changes in traffic pace have an impact on food choices (such as through commuting time taking away from grocery shopping and cooking, thus resulting in poorer food quality choices), then that would be informative in providing a more complete, not only pecuniary, but physical and mental health related cost estimate of neighborhood effects. Furthermore, it could also contribute to our understanding of the heterogeneity of the impact of neighborhood characteristics across the population.

The costs of mental ill health and ill-being are an enormous burden in most contemporary economies, yet the economic understanding of these variables is less than complete. This thesis contributes to such improved understanding through the study of these factors in the United Kingdom, doing so with unique, geo-spatial panel data. The findings in each chapter suggest that such previously-unaccounted or less precisely accounted for costs are substantial and informative for policy; as well as suggesting that further studies in this direction would be fruitful in furnishing more precise economic accounts, and in understanding paths through which the easing of such burdens can occur.

Bibliography

Alesina, A., R. Di Tella, and R. MacCulloch (2004). Inequality and happiness: are Europeans and Americans different? *Journal of Public Economics 88*(9-10), 2009–2042.

Almeida, D. M., E. Wethington, and R. Kessler (2002). The daily inventory of stressful events: An interview-based approach for measuring daily stressors. *Assessment 9*(1), 41–55.

Altman, D. G. and P. Royston (2006). The cost of dichotomising continuous variables. *BMJ 332*(7549), 1080.

Baetschmann, G., K. E. Staub, and R. Winkelmann (2015). Consistent estimation of the fixed effects ordered logit model. *Journal of the Royal Statistical Society: Series A (Statistics in Society) 178*(3), 685–703.

Baudains, P., A. Braithwaite, and S. D. Johnson (2013). Target choice during extreme events: A discrete spatial choice model of the 2011 London Riots. *Criminology 51*(2), 251–285.

BBC News (2011). England riots: Broken society is top priority - Cameron. http://www.bbc.co.uk/news/uk-politics-14524834. Date accessed: May 15, 2016.

Becker, G. S. (1968). Crime and punishment: An economic approach. *The economic dimensions of crime pp. 13-68*.

Becker, G. S. and Y. Rubinstein (2004). Fear and the response to terrorism: An economic analysis. Report, University of Chicago mimeo.

Bell, B., L. Jaitman, and S. Machin (2014). Crime deterrence: Evidence from the london 2011 riots. *The Economic Journal 124*(576), 480–506.

Bencsik, P. (2018). The non-financial costs of violent public disturbances: Emotional responses to the 2011 riots in England. *Journal of Housing Economics 40*, 73–82.

Bertolote, J. (2008). The roots of the concept of mental health. *World psychiatry : official journal of the World Psychiatric Association (WPA) 7*(2), 113–116.

Birch, E. E., S. Garfield, D. R. Hoffman, R. Uauy, and D. G. Birch (2000). A randomized controlled trial of early dietary supply of long-chain polyunsaturated fatty acids and mental development in term infants. *Developmental medicine and child neurology 42*(3), 174–181.

Blanes i Vidal, J., L. Bolte, and T. Kirchmaier (2017). Domestic abuse: What do we know about it?. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2867580.

Bloom, D. E., E. Cafiero, E. Jané-Llopis, S. Abrahams-Gessel, L. R. Bloom, F. A. B. Fathima, S., T. Gaziano, A. Hamandi, M. Mowafi, and D. O'Farrell (2012). The global economic burden of noncommunicable diseases. *Program on the Global Demography of Aging. No. 8712*.

Bor, J., A. S. Venkataramani, D. R. Williams, and A. C. Tsai (2018). Police killings and their spillover effects on the mental health of black Americans: a population-based, quasi-experimental study. *The Lancet 392*(10144), 302–310.

Bourguignon, F. (1999). The cost of children: may the collective approach to household behavior help? *Journal of Population Economics 12*(4), 503–521.

Bourque, L. B., L. A. Russell, and J. D. Goltz (1993). Human behavior during and immediately after the earthquake. *The Loma Prieta, California, Earthquake of October 17*(1989), B3–B22.

Braakmann, N. (2012). How do individuals deal with victimization and victimization risk? Longitudinal evidence from Mexico. *Journal of Economic Behavior & Organization 84*(1), 335–344.

Bradbury, B. (2008). Time and the cost of children. *Review of Income and Wealth 54*(3), 305–323.

Briggs, D. (2012). *The English Riots of 2011: A Summer of Discontent. In: Frustrations, urban relations and temptations*, pp. 27. Waterside Press.

Bruni, L. and R. Sugden (2007). The road not taken: how psychology was removed from economics, and how it might be brought back. *The Economic Journal 117*(516), 146–173.

Bryson, A. and G. MacKerron (2017). Are you happy while you work? *The Economic Journal 127*(599), 106–125.

Bryson, A. and G. MacKerron (2018). How does terrorism affect individuals' wellbeing?.

Buddelmeyer, H., D. S. Hamermesh, and M. Wooden (2018). The stress cost of children on moms and dads. *European Economic Review 109*, 148–161.

Camacho, A. (2008). Stress and birth weight: evidence from terrorist attacks. *American Economic Review 98*(2), 511–15.

Campbell, R. J. (2004). *Campbell's psychiatric dictionary*. Oxford University Press.

Centre for Economics and Business Research (2014). Cost of child hits £227,266. *Centre for Economics and Business Research*. www.cebr.com/reports/cost-of-raising-a-child-hits-227266-with-families-feeling-the-impact-of-benefit-cuts/.

Charles, S. T., J. R. Piazza, M. Slwinski, J. Mogle, and D. M. Almeida (2013). The wear-and-tear of daily stressors on mental health. *Psychological Science 24*, 733–741.

Clark, A., E. Diener, Y. Georgellis, and R. Lucas (2008). Lags and leads in life satisfaction: A test of the baseline hypothesis. *Economic Journal 118*(529), F222–F243.

Clark, A., S. Flèche, R. Layard, N. Powdthavee, and G. Ward (2017). *The Origins of Happiness: The Science of Well-Being over the Life Course*. Princeton University Press.

Clark, A. E. and A. J. Oswald (2002). Well-being in panels. *DELTA, mimeo*.

Clark, D. M. (2011). Implementing NICE guidelines for the psychological treatment of depression and anxiety disorders: the IAPT experience. *International Review of Psychiatry 23*(4), 318–327.

Cnop, M., F. Foufelle, and L. A. Velloso (2012). Endoplasmic reticulum stress, obesity and diabetes. *Trends in molecular medicine 18*(1), 59–68.

Cornaglia, F., N. E. Feldman, and A. Leigh (2014). Crime and mental well-being. *Journal of Human Resources 49*(1), 110–140.

Cullen, J. B. and S. D. Levitt (1999). Crime, urban flight, and the consequences for cities. *The Review of Economics and Statistics 81*(2), 159–169.

Di Tella, R., L. Freira, R. H. Gálvez, E. Schargrodsky, D. Shalom, and M. Sigman (2019). Crime and violence: Desensitization in victims to watching criminal events. *Journal of Economic Behavior & Organization 159*(C), 613–625.

Di Tella, R., R. J. MacCulloch, and A. J. Oswald (2003). The macroeconomics of happiness. *Review of Economics and Statistics 85*(4), 809–827.

Dickerson, A., A. R. Hole, and L. A. Munford (2014). The relationship between well-being and commuting revisited: Does the choice of methodology matter? *Regional Science and Urban Economics 49*, 321–329.

Diener, E. (2012). Do hedonic measures differ from cognitive evaluation measures of well-being? *Background Paper for National Academy of Sciences Panel on Well-Being Metrics and Public Policy*.

Dolan, P., R. Layard, and R. Metcalfe (2011). Measuring subjective well-being for public policy. http://eprints.lse.ac.uk/35420/1/measuring-subjective-wellbeing-for-public-policy.pdf.

Dolan, P., T. Peasgood, and M. White (2008). Do we really know what makes us happy? A review of the economic literature on the factors associated with subjective well-being. *Journal of Economic Psychology 29*(1), 94–122.

Doleac, J. L. and N. J. Sanders (2015). Under the cover of darkness: How ambient light influences criminal activity. *Review of Economics and Statistics 97*(5), 1093–1103.

Draca, M., S. Machin, and R. Witt (2011). Panic on the streets of london: Police, crime, and the july 2005 terror attacks. *American Economic Review 101*(5), 2157–81.

Duffy, B., R. Wake, T. Burrows, and P. Bremner (2008). Closing the gaps–crime and public perceptions. *International Review of Law, Computers & Technology 22*(1-2), 17–44.

Dustmann, C. and F. Fasani (2016). The effect of local area crime on mental health. *The Economic Journal 126*(593), 978–1017.

Easterlin, R. A. (1974). Does economic growth improve the human lot? Some empirical evidence. *In P. David M. W. Reder (Eds.), Nations and Households in Economic Growth: Essays in Honour of Moses Abramovitz. New York: Academic Press*, 89–125.

Evenson, R. J. and R. W. Simon (2005). Clarifying the relationship between parenthood and depression. *Journal of Health and Social Behavior 46*, 341–358.

Ferrer-i Carbonell, A. and P. Frijters (2004). How important is methodology for the estimates of the determinants of happiness? *The Economic Journal 114*(497), 641–659.

Folbre, N. (1994). Children as public goods. *American Economic Review 84*(2), 86–90.

Frey, B. and A. Stutzer (2014). Economic consequences of mispredicting utility. *Journal of Happiness Studies 15*(4), 937–956.

Frey, B. S. and A. Stutzer (2000). Happiness, economy and institutions. *The Economic Journal 110*(466), 918–938.

Frijters, P., D. Johnston, and M. Shields (2011). Life satisfaction dynamics with quarterly life event data. *Scandinavian Journal of Economics 113*(1), 190–211.

Gibbons, S. (2004). The costs of urban property crime. *The Economic Journal 114*(499), F441–F463.

Greenbaum, R. T. and G. E. Tita (2004). The impact of violence surges on neighbourhood business activity. *Urban Studies 41*(13), 2495–2514.

Grundy, E. and M. Jitlal (2007). Socio-demographic variations in moves to institutional care 1991–2001: a record linkage study from England and Wales. *Age and ageing 34*(4), 424–430.

Grundy, E. and S. Read (2012). Social contacts and receipt of help among older people in England: are there benefits of having more children? *Journals of Gerontology Series B: Psychological Sciences and Social Sciences 67*(6), 742–754.

Gustafsson, B. and U. Kjulin (1994). Time use in child care and housework and the total cost of children. *Journal of Population Economics 7*(3), 287–306.

Haller, M. and M. Hadler (2006). How social relations and structures can produce happiness and unhappiness: An international comparative analysis. *Social Indicators Research 75*, 169–216.

Hamermesh, D. S. (1999). Crime and the timing of work. *Journal of Urban Economics 45*(2), 311–330.

Hankins, M. (2008). The factor structure of the twelve item General Health Questionnaire (GHQ-12): the result of negative phrasing? *Clinical Practice and Epidemiology in Mental Health 4*(1), 10.

Hanson, R. F., D. G. Kilpatrick, J. R. Freedy, and B. E. Saunders (1995). Los Angeles County after the 1992 civil disturbances: degree of exposure and impact on mental health. *Journal of Consulting and Clinical Psychology 63*(6), 987.

Hardy, G. E., D. A. Shapiro, C. E. Haynes, and J. E. Rick (1999). Validation of the General Health Questionnaire-12: Using a sample of employees from England's health care services. *Psychological Assessment 11*(2), 159.

Hays, J., C. Pieper, and J. Purser (2003). Competing risk of household expansion or institutionalization in late life. *The journals of gerontology series B: psychological Sciences and Social Sciences 58*(1), S11–S20.

Health and Safety Executive (2017). Work-related stress, depression or anxiety statistics in Great Britain 2017. http://www.hse.gov.uk/statistics/causdis/stress/stress.pdf.

Herane-Vives, A., V. de Angel, A. Papadopoulos, T. Wise, K.-C. Chua, R. Strawbridge, D. Castillo, D. Arnone, A. H. Young, and A. J. Cleare (2018). Short-term and long-term measures of cortisol in saliva and hair in atypical and non-atypical depression. *Acta Psychiatrica Scandinavica 137*(3), 216–230.

Hicks, S., L. Tinkler, and P. Allin (2013). Measuring subjective well-being and its potential role in policy: Perspectives from the UK office for national statistics. *Social Indicators Research 114*(1), 73–86.

Hipp, J. R. (2010). A dynamic view of neighborhoods: The reciprocal relationship between crime and neighborhood structural characteristics. *Social Problems 57*(2), 205–230.

Hole, A. R., A. Dickerson, and L. Munford (2011). A review of estimators for the fixed-effects ordered logit model. *United Kingdom Stata Users' Group Meetings 2011. 5*. https://ideas.repec.org/p/boc/usug11/05.html.

Huizink, A. C., P. G. Robles de Medina, E. J. Mulder, G. H. Visser, and J. K. Buitelaar (2003). Stress during pregnancy is associated with developmental outcome in infancy. *Journal of Child Psychology and Psychiatry 44*(6), 810–818.

Ingram, R. E. and D. D. Luxton (2005). *Fear of crime and criminal victimization: Gender-based contrasts*. Vulnerability-stress models. Development of psychopathology: A vulnerability-stress perspective, 46. SAGE Publications.

Institute for Economics & Peace (2013). UK Peace Index: Exploring the fabric of peace in the UK from 2003 to 2012. http://economicsandpeace.org/wp-content/uploads/2015/06/UK_Peace_Index_report_2013_0.pdf.

Jackson, J. and M. Stafford (2009). Public health and fear of crime: A prospective cohort study. *The British Journal of Criminology 49*(6), 832–847.

James, N. (2018). Recent Violent Crime Trends in the United States. *Congressional Research Service R45236*.

Janke, K. M., C. Propper, and M. A. Shields (2016). Assaults, murders and walkers: The impact of violent crime on physical activity. *Journal of health economics 47*, 34–49.

Juster, F. T. (1985). Time, Goods, and Well-Being. In: F. Juster, F. Stafford, Eds. Institute for Social Research, Ann Arbor, MI. pp. 397–414.

Kahneman, D., A. Krueger, D. Schkade, N. Schwarz, and A. Stone (2004). A survey method for characterizing daily life experience: The day reconstruction method. *Science 306*(5702), 1776–1780.

Kahneman, D. and R. Thaler (2006). Anomalies: Utility maximization and experienced utility. *Journal of Economic Perspectives 20*(1), 221–234.

Katz, L. F., J. R. Kling, and J. B. Liebman (2001). Moving to opportunity in Boston: Early results of a randomized mobility experiment. *The Quarterly Journal of Economics 116*(2), 607–654.

Kawalerowicz, J. and M. Biggs (2015). Anarchy in the UK: Economic deprivation, social disorganization, and political grievances in the London riot of 2011. *Social Forces 94*(2), 673–698.

Kirchmaier, T. and C. Villa Llera. Murders in London. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3211350.

Kling, J. R., J. B. Liebman, and L. F. Katz. (2007). Experimental analysis of neighborhood effects. *Econometrica 75*(1), 83–119.

Kohler, H., J. Behrman, and A. Skytthe (2005). Partner+ Children= Happiness? The Effects of Partnerships and Fertility on Well-Being. *Population and Development Review 31*(3), 407–445.

Lachman, S. J. (1996). Psychological perspective for a theory of behavior during riots. *Psychological reports 79*(3), 739–744.

Larsson, K. and M. Silverstein (2004). The effects of marital and parental status on

informal support and service utilization: A study of older Swedes living alone. *Journal of Aging Studies 18*(2), 231–244.

Laville, S., P. Lewis, V. Dodd, and C. Davies (2011). Doubts emerge over Duggan shooting as London burns. *The Guardian 8*. https://www.theguardian.com/uk/2011/aug/07/police-attack-london-burns. Access date: May 15, 2016.

Layard, R. (2005). Mental health: Britain's biggest social problem? http://eprints.lse.ac.uk/47428/1/__Libfile_repository_Content_Layard_Mental%20health%20Britain%E2%80%99s%20biggest%20social%20problem%28lsero%29_Mental%20health%28lsero%29.pdf.

Layard, R. (2006). Happiness and Public Policy: a Challenge to the Profession. *The Economic Journal 116*, C24–C33.

Layard, R. (2017). The economics of mental health. *IZA World of Labor 321*.

Lelkes, O. (2006). Knowing what is good for you. Empirical analysis of personal preferences and the "objective good". *The Journal of Socio-Economics 35*, 285–307.

Lewis, P., T. Newburn, M. Taylor, C. Mcgillivray, A. Greenhill, H. Frayman, and R. Proctor (2011). Reading the riots: Investigating England's summer of disorder. https://eprints.lse.ac.uk/46297/1/Reading%20the%20riots%28published%29.pdf.

Linden, L. and J. E. Rockoff (2008). Estimates of the impact of crime risk on property values from Megan's laws. *American Economic Review 98*(3), 1103–27.

Lino, M., K. Kuczynski, N. Rodriguez, and T. Schap (2017). Expenditures on Children by Families, 2015. *Miscellaneous Publication No. 1528-2015. U.S. Department of Agriculture, Center for Nutrition Policy and Promotion*.

Loewenstein, G., T. O'Donoghue, and M. Rabin (2003). Projection bias in predicting future utility. *The Quarterly Journal of Economics 118*(4), 1209–1248.

Ludwig, J., G. J. Duncan, L. A. Gennetian, L. F. Katz, R. C. Kessler, J. R. Kling, and L. Sanbonmatsu. (2012). Neighborhood effects on the long-term well-being of low-income adults. *Science 337*(6101), 1505–1510.

MacKerron, G. (2012). *Happiness and environmental quality.* Ph. D. thesis. http://etheses.lse.ac.uk/383/1/Mackerron%20happiness%20and%20environmental%20quality%20%28public%20version%29.pdf.

McEwen, B. S. (1998). Stress, adaptation, and disease: Allostasis and allostatic load. *Annals of the New York academy of sciences 840*(1), 33–44.

McLanahan, S. and J. Adams (1987). Parenthood and psychological well-being. *Annual review of sociology 13*(1), 237–257.

Messer, L. C., J. S. Kaufman, N. Dole, A. Herring, and B. A. Laraia (2006). Violent crime exposure classification and adverse birth outcomes: a geographically-defined cohort study. *International Journal of Health Geographics 5*(1), 22.

Metcalfe, R., N. Powdthavee, and P. Dolan (2011). Destruction and distress: Using a quasi-experiment to show the effects of the september 11 attacks on mental well-being in the united kingdom. *The Economic Journal 121*(550), F81–F103.

Miller, T. R., M. A. Cohen, and S. B. Rossman (1993). Victim costs of violent crime and resulting injuries. *Health Affairs 12*(4), 186–197.

Ministry of Justice (2012). Statistical bulletin on the public disorder of 6th to 9th August 2011 - September 2012 update. https://www.gov.uk/government/statistics/statistical-bulletin-on-the-public-disorder-of-6th-9th-august-2011--2.

Moore, A. (2011). Riots in Tottenham after Mark Duggan shooting protest. https://www.bbc.co.uk/news/uk-england-london-14434318.

Morales, J. R. and N. G. Guerra (2006). Effects of multiple context and cumulative stress on urban children's adjustment in elementary school. *Child development 77*(4), 907–923.

Muaremi, A., B. Arnrich, and G. Tröster (2012). A Survey on Measuring Happiness with Smart Phones. *Conference: 6th International Workshop on Ubiquitous Health and Wellness*. https://www.researchgate.net/profile/Bert_Arnrich/publication/235834264_A_Survey_on_Measuring_Happiness_with_Smart_Phones/links/0fcfd513f50c5229f9000000.pdf.

Muellbauer, J. (1977). Testing the Barten model of household composition effects and the cost of children. *Economic Journal 87*(347), 460–487.

Nelson, S., K. Kushlev, T. English, E. Dunn, and S. Lyubomirsky (2013). In defense of parenthood: Children are associated with more joy than misery. *Psychological Science 24*(1), 3–10.

Newton-Small, J. (2011). After the Riots: the Economic Cost of London's Mayhem. *Time*. http://world.time.com/2011/08/12/after-the-riots-the-economic-cost-of-londons-mayhem/.

Nomaguchi, K. M. and M. A. Milkie (2003). Costs and rewards of children: The effects of becoming a parent on adult's lives. *Journal of Marriage and Family 65*, 356–374.

Odermatt, R. and A. Stutzer (2019). (Mis-)Predicted Subjective Well-Being Following Life Events. *Journal of the European Economic Association 17*(1), 245–283.

Office for National Statistics (2015). Stress policy. https://www.ons.gov.uk/aboutus/transparencyandgovernance/freedomofinformationfoi/stresspolicy.

Office for National Statistics (2017). Public perceptions of crime in England and Wales: year ending March 2016. https://www.ons.gov.uk/peoplepopulationandcommunity/

crimeandjustice/articles/publicperceptionsofcrimeinenglandandwales/yearendingmarch2016.

Office for National Statistics (2018). Crime in England and Wales: year ending December 2017. https://www.ons.gov.uk/peoplepopulationandcommunity/crimeandjustice/bulletins/crimeinenglandandwales/yearendingdecember2017.

Peasgood, T. M. (2008). *Measuring well-being for public policy.* Thesis. https://spiral.imperial.ac.uk/bitstream/10044/1/5475/1/Peasgood-%20TM-2009-%20PhD-Thesis.pdf.

Perry, R. W., M. K. Lindell, and K. J. Tierney (2001). *Facing the unexpected: Disaster preparedness and response in the United States*, pp. 321. Joseph Henry Press.

Piazza, J. R., S. T. Charles, M. Sliwinski, J. Mogle, and D. M. Almeida (2013). Affective reactivity to daily stressors and long-term risk of reporting a chronic physical health condition. *Annals of Behavioral Medicine 45*.

Pollak, R. A. and T. J. Wales (1979). Welfare comparisons and equivalence scales. *The American Economic Review. 69*(2), 216–221.

Powdthavee, N. (2008). Putting a price tag on friends, relatives, and neighbours: Using surveys of life satisfaction to value social relationships. *Journal of Socio-Economics 37*(4), 1459–1480.

Pronzato, C. (2011). British Household Panel Survey Consolidated Marital, Cohabitation and Fertility Histories, 1991-2009 (computer file)., 3rd Edition. *University of Essex. Institute for Social and Economic Research, (original data producer(s)). Colchester, Essex: UK Data Archive (distributor)*, https://doc.ukdataservice.ac.uk/doc/5629/mrdoc/pdf/5629userguide.pdf.

Reeves, A. and R. de Vries (2016). Does media coverage influence public attitudes towards welfare recipients? The impact of the 2011 English riots. *The British Journal of Sociology 67*(2), 281–306.

Ross, C. E. and J. Mirowsky (2001). Neighborhood disadvantage, disorder, and health. *Journal of Health and Social Behavior 42*(3), 258–276.

Rubin, G. J., C. R. Brewin, N. Greenberg, J. Simpson, and S. Wessely (2005). Psychological and behavioural reactions to the bombings in London on 7 July 2005: cross sectional survey of a representative sample of Londoners. *BMJ 331*(7517), 606.

Rufrancos, H., M. Power, K. E. Pickett, and R. Wilkinson (2013). Income Inequality and Crime: A Review and Explanation of the Time-series Evidence. *Sociology and Criminology-Open Access*.

Schafer, J. A., H. B. M. and T. S. Bynum (2006). Fear of crime and criminal victimization: Gender-based contrasts. *Journal of Criminal Justice 34*(3), 285–301.

Schonfeld, P., J. Brailovskaia, A. Bieda, X. Zhang, and J. Margraf (2016). The effects of daily stress on positive and negative mental health: Mediation through self-efficacy. *International Journal of Clinical and Health Psychology 16*(1), 1–10.

Shanks, T. R. W. and C. Robinson (2013). Assets, economic opportunity and toxic stress: A framework for understanding child and educational outcomes. *Economics of Education Review 33*, 154–170.

Sharkey, P., A. E. Schwartz, I. G. Ellen, and J. Lacoe (2014). High stakes in the classroom, high stakes on the street: The effects of community violence on student's standardized test performance. *Sociological Science 1*, 199–220.

Smith, A., Y. Oluboyede, R. West, J. Hewison, and A. House (2013). The factor structure of the GHQ-12: The interaction between item phrasing, variance and levels of distress. *Quality of Life Research 22*(1), 145–152.

Smolej, M. and J. Kivivuori (2006). The relation between crime news and fear of violence. *Journal of Scandinavian Studies in Criminology and Crime Prevention 7*(2), 211–227.

Soni, A. (2009). The Five Most Costly Conditions, 1996 and 2006: Estimates for the U.S. Civilian Noninstitutionalized Population. *Agency for Healthcare Research and Quality, Rockville, MD. Statistical Brief 248.*(July).

Stafford, M., T. Chandola, and M. Marmot (2007). Association between fear of crime and mental health and physical functioning. *American Journal of Public Health 97*(11), 2076–2081.

Steel, M. (2016). Measuring National Wellbeing in the United Kingdom. *Office for National Statistics*.

Telegraph (2011). London riots: Prime Minister's statement in full. http://www.telegraph.co.uk/news/uknews/crime/8691034/London-riots-Prime-Ministers-statement-in-full.html. Access date: May 15, 2016.

The Guardian (2011). Kenneth Clarke blames English riots on a "broken penal system". https://www.theguardian.com/uk/2011/sep/05/kenneth-clarke-riots-penal-system Access date: May 15, 2016.

Tita, G. E., T. L. Petras, and R. T. Greenbaum (2006). Crime and residential choice: a neighborhood level analysis of the impact of crime on housing prices. *Journal of Quantitative Criminology 22*(4), 299.

Trautmann, S., J. Rehm, and H. U. Wittchen (2016). The economic costs of mental disorders: Do our societies react appropriately to the burden of mental disorders? *EMBO reports 17*(9), 1245–1249.

Tversky, A. and D. Kahneman (1974). Judgment under uncertainty: Heuristics and biases. *Science 185*(4157), 1124–1131.

Twenge, J. M., W. K. Campbell, and C. A. Foster (2003). Parenthood and marital satisfaction: a meta-analytic review. *Journal of Marriage and Family 65*(3), 574–583.

Wellings, K., K. G. Jones, C. H. Mercer, C. Tanton, S. Clifton, J. Datta, A. J. Copas, B. Erens, L. J. Gibson, W. Macdowall, P. Sonnenberg, A. Phelps, and A. M. Johnson (2013). The prevalence of unplanned pregnancy and associated factors in Britain: findings from the third National Survey of Sexual Attitudes and Lifestyles (Natsal-3). *Lancet (London, England) 382*(9907), 1807–16.

Wessely, S. and P. J. Taylor (1991). Madness and crime: Criminology versus psychiatry. *Criminal Behaviour and Mental Health 1*, 193–228.

White, M. and P. Dolan (2009). Accounting for the richness of daily activities. *Psychological Science 20*(8), 1000–1008.

Wilbert-Lampen, U., D. Leistner, S. Greven, T. Pohl, S. Sper, C. Völker, D. Güthlin, A. Plasse, A. Knez, H. Küchenhoff, and G. Steinbeck (2008). Cardiovascular events during World Cup soccer. *New England Journal of Medicine 358*(5), 475–483.

Wilson, T. and T. Gilbert (2003). Affective Forecasting. *Advances in Experimental Social Psychology 35*, 345–411.

Wilson, T. and T. Gilbert (2013). The Impact Bias Is Alive and Well. *Journal of Personality and Social Psychology 105*(5), 740–748.